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AUTOMATED VALUATION MODELS (AVMs) IN COMMERCIAL REAL ESTATE MARKET

Master's Thesis

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Abstract of master's thesis

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Abstract

Automated valuation models (AVMs) have gained popularity and widely adopted in many research domains. In residential real estate, AVMs have been used to predict the price of houses, apartments and increasingly showed their effectiveness. Their advantages are ranging from speed, accuracy to consistency and inexpensiveness. However, in commercial real estate, AVMs have been remained under development phase due to the fact that commercial properties are heterogeneous and irregularly traded in the market. Therefore, this thesis aims to contribute to the development of AVMs for commercial real estate. Literature review and valuation theories are first examined in order to determine what factors should be included in AVMs. Further, the thesis demonstrates how AVMs could be developed under two different market circumstances by utilizing all possible data sources.

The findings show that in the first empirical case where the sales-comparison approach is used, property physical attributes, locational factors, and economic factors all affect property values. Thus, they should be included in the AVM development. In the second empirical case where income approach is used, property's finance information such as cash inflows and outflows are key for valuation accuracy. In order to use fully automated valuation model for the second case, rental models and overall capitalization rate models should be researched further.

Keywords Automated Valuation Models, AVMs, Commercial Real Estate, Office Property, Real Estate Valuation

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Espoo, 27 May 2019

Diem Nguyen

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Chapter 1: Introduction

1.1 Background and motivation

Real estate business accounts for 60% of all global mainstream assets (Savills, 2016), thereby remaining as an inevitable asset class in any institutional investor's portfolio. This fact means all related parties including investors, financial institutions and even the government continuously try to get a clearer understanding of current and future values of real estate assets. Meanwhile, traditional property valuation is conducted manually and case by case which requires a lot of time to get a proper appraisal. The valuation process usually takes weeks from initial assignment to final report. Therefore, the traditional way of property valuation is not only pricy and time-consuming but also subjected to human errors and biases.

Digitalization is one of the most powerful megatrends that fundamentally changes our way of working and investing. Advances in technology, data and analytics have reshaped the industry landscape and benefitted players in many facets. In fact, according to Fidelity Global Institutional Investor Survey (2018), 79% of institutional investors believed Artificial Intelligence (AI) such as algorithms and quantitative models will make markets and decision-making more accurate and efficient. The development of the data-driven models in ways that ascertains the value of property attributes and examines their degree of each contribution to the value formation of the property is essential. Modeling techniques for assessing large scale data estimate the property value consistently, thereby producing fair results over subjective biases. Moreover, these models improve the efficiency and effectiveness of the process of real estate appraisal with low cost, high speed with actionable information by utilizing the power of statistical application in an automated way. As opposed to rising concerns that these automated models would replace the role of human, the industry still appreciates the expertise and vital insights of portfolio managers. Automated valuation models, instead, are great tools that complement their daily work and provide greater efficiency for all stakeholders.

Automated valuation models (AVMs) have gained popularity and widely adopted in many research domains and industries. AVMs have been mainly used to predict the price of houses, apartments, residential properties and increasingly showed their effectiveness. However, there are very few applications of AVMs in the field of commercial real estate. The reason is that AVMs require both quantity and quality of the data source as inputs, whereas commercial properties are infrequently traded in the market and hence there are not many comparable data available. This is not to mention the fact that factors used to determine commercial property values vary significantly. For instance, for residential sector attributes affecting the price are fairly similar (i.e. size, number of rooms, condition, etc.) whereas this is not always the case in commercial real estate. An example of this is that a number of docks and bays are relevant for industrial properties but irrelevant for the office asset class.

Therefore, AVMs in commercial real estate have remained under the development phase even though the first sign of AVMs already introduced in the 1960s (Rossini & Kershaw, 2008). This thesis aims to bridge the gap by developing AVMs for Commercial real estates based on the existing approaches and theory of various determinants of commercial property values.

1.2 Objectives and research questions

This thesis aims to develop AVMs for commercial property in two different market dimensions, including the United States and Finland using regression method for the former and discounted cash flows for the latter. According to Metzner & Kindt (2017), there are four general types of modeling in model specification. Those are sales-comparison approach, cost approach, income approach, and hedonic price method. Among all, hedonic price models are the most common basis for constructing AVMs. Nevertheless, real estate market is sometimes very inefficient and localized. Consequently, developing an AVM with one specific model specification that expectedly works in every kind of market is not realistic because what works in one market does not guarantee it will work in another. Rather, the process of developing AVM and model specification should highly depend on the characteristics of the local market, data availability, and data characteristics.

There are many debates over whether commercial property is far more complicated and way heterogeneous to be modeled. In addition, commercial property data is usually limited in order to develop AVMs. Nevertheless, this study proposes ways to do so by utilizing all possible data sources available. These include:

- Property physical characteristics for example age, size, condition, types of property
- Property's financial data for example cash inflows, cash outflows, vacancy rates
- Regional economic characteristics for example urbanization rate, population density, proximity, and accessibility
- Economic trends for example GDP, inflation, interest rate, money supply, and housing price index (HPI).

The goal of this thesis is to develop an AVM for each market dimension that predicts fairly accurate property values. The research problems can be fully addressed using three following research questions and sub-questions:

- **What parameters should be included in AVMs?**
    - What constitutes property values?
- **How an AVM could be developed?**
    - What would be a suitable approach for property valuation under different market circumstances?

    - What would be the set of information that could be utilized in the market under research?
- **Should Automated Valuation Models be used to enhance decision making by real estate market players?**

In the first question, literature and theory is reviewed in order to find appropriate parameters for AVMs. The second question focuses on two case studies and demonstrating the process of developing AVMs. The third question provides accuracy and reliability by testing the model's outputs with benchmark values.

1.3 Research methodology

This research consists of two parts which are literature review and empirical study. The research starts with a literature review which aims firstly to give audiences a broad view of AVMs and how these could be effectively used to tackle the traditional property appraisal, secondly to establish theory foundation of relevant variables that are used in the AVM and support the method used in the AVM development process.

The empirical research includes two case studies where property tax appraisal values (in the United States) and transaction price (in Finland) are quantitatively evaluated. The research method used in this thesis is a statistical approach which assessed values of more than 140 000 individual property in the United States and twelve individual properties in Finland with different model specifications. The empirical research methods are described in Chapter 4.

1.4 Structure of the research

The thesis comprises five chapters that cover the topics and answers above-mentioned research questions. The structure of the research is presented in table 1 in the below:

Chapter	Content	Purpose
1	Introduction	To introduce the research topic
2	Automated valuation models (AVMs) and their application in the field of real estate	To review the application state of AVMs, their advantages and advantages
3	Determinants of commercial property values	To establish a strong theoretical foundation about parameters that are used in AVMs
4	Empirical research	To introduce the process of developing AVMs in two different markets
5	Conclusion	To discuss the results of the study and propose topics for further research

Table 1: Structure of the Research

The first chapter Introduction provides audiences background and motivations of the research, objectives, research questions, research methodology, and structure of the research.

The second chapter outlines AVMs definition, application states, advantages, and disadvantages, as long as AVMs development process and challenges of developing AVMs in commercial real estate. The third chapter presents the real estate valuation methods and groups of factors that influence property prices. After that, the fourth chapter demonstrates data collection, model specification and model validation in two case studies. The final chapter discusses the results and suggests potential topics that could be conducted in the future.

Chapter 2: Automated valuation models (AVMs) and their application in the field of real estate

2.1 Definition of Automated Valuation Models

Automated Valuation Models (AVMs) have gained more and more popularity in real estate domain in the 21st century. Not only are academics interest in the use of AVMs, but also among practitioners, constructing accurate and reliable AVMs are more captivating than ever. In some real estate appraisal companies, owning credible AVMs equals to gaining competitive advantages over rivals regarding speed, cost-effectiveness, and appraisal value consistency.

The first signs of AVMs had its origin in North America, and although the first commercial application happened in 1981 (Matysiak, 2017) AVM has just become popular in some of the very last years of the 20th century (Donovan, 2015). The nature of AVMs definition had been slightly changed along with time. International Association of Assessing Officers, IAAO (2003, p. 5) defined AVM as:

> "A mathematically based *computer software programme* that produces an estimate of market value based on analysis of location, market conditions, and real estate characteristics from information collected. The distinguishing feature of an AVM is that it produces a market valuation through *mathematical modeling.*"

TEGoVA defined AVMs in their European Valuation Standards EVIP 6 as:

"*Statistic-based computer programmes*, which use property information (e.g. comparable sales and property characteristics etc.) to generate property-related values or suggested values." (TEGoVA, 2016, p. 325)

The definitions around this time of period considered AVMs as mathematical-based methods using computer technicalities to predict the values of properties. Moving on the later timeline, AVMs's definitions are more emphasized with the automation and without human interference in the process of producing one estate's value.

Furthermore, AVMs are regarded as:

"*Statistical valuation solutions* providing an estimate of value of any specified property at a specified date, using sophisticated modeling techniques in an *automated manner* and typically including a comparable-based approach similar to surveyor valuations." (European AVM Alliance & European Mortgage Federation, 2016, p. 1)

Much in common, three definitions all point out that AVMs are mathematical methods leveraging computer technicalities, with the aid of the high amount of transactions in the process of suggesting values of properties automatically and efficiently *without* human interaction. As stated by Donovan (2015), in addition, the term AVMs was used among academics and practitioners indicating the high level of automation of the predicted models. Moreover, valuations provided by AVMs are usually accompanied by a confidence level indicating the degree of accuracy and reliability of those estimations (d'Amato, 2017)

The underlying method of AVMs in predicting the price of one property was not identified exactly but more generic in most of the definitions. For example, IAAO (2003) mentioned "a mathematically based computer software programme", or "statistic-based computer programmes" (TEGoVA, 2016) or "Statistical valuation solutions" (European AVM Alliance & European Mortgage Federation, 2016). In common practice, there have been a lot of methods applied to build models. Generally, the most popular and perhaps most traditional method in AVMs specification is the hedonic pricing method. However, since the computer power regarding doing the calculation is increasingly enhanced together with the growth of technology trend, more and more advanced mathematical methods are researched in developing AVMs. The method of constructing AVM mathematical modeling is diversified ranging from econometrics, over data mining to machine learning.

Like other appraisals, final outputs of AVMs, in most of assignments, are the market value of real estate (Mooya, 2017). Market value is one of the most important concept and mostly used in real estate transaction in the market. Although, IVSC (2017, p. 18) defined the term market value as "the estimated amount for which an asset or liability should exchange on the valuation date between a willing buyer and willing seller in an arm's length transaction, after proper marketing and where the parties had each acted knowledgeably, prudently and without compulsion", IAAO (2003, p. 33) addressed market value – i.e. AVM's output is "the most probable price (in terms of money) that a property should bring in a competitive and open market under the conditions requisite to a fair sale". Market value or most likely price of a given real estate possibly is the most desirable information that involved participant wish to know.

IAAO (2003) draws the distinction between AVMs and traditional is that while AVMs produce value estimation automatically by the use of statistical and mathematically application, whereas traditional appraisal relies on human valuers. In order to derive property value, an appraiser will conduct physical inspections and analyze property data based on his judgment and experience.

AVM versus CAMA

For the sake of eliminating confusing jargon, it is important to differentiate Automated Valuation Model (AVM) from Computer Assisted Mass Appraisal (CAMA) or Mass Appraisal – another counterpart system leverages the use of computing technicalities in real estate assessment. AVM and CAMA (or Mass Appraisal) all use mathematical techniques with the aid of big property transaction database to evaluate real estate assets. However, CAMA (or Mass Appraisal) is used for a larger group of properties. The purpose of using CAMA is mainly for taxation at a specific time (d'Amato, 2017). On the other hand, AVMs are employed in various scales ranging from single valuation over batch valuation (i.e. include several properties) to portfolio valuation (i.e. involving many properties) (Metzner & Kindt, 2017). The application of AVMs is widely adopted in many domains such as capital requirement purpose, covered bonds and securitization transactions, investment property fund, asset management, risk management, and so on (EMF & EAA, 2016). The comparison between AVM and CAMA was illustrated in the bellows;

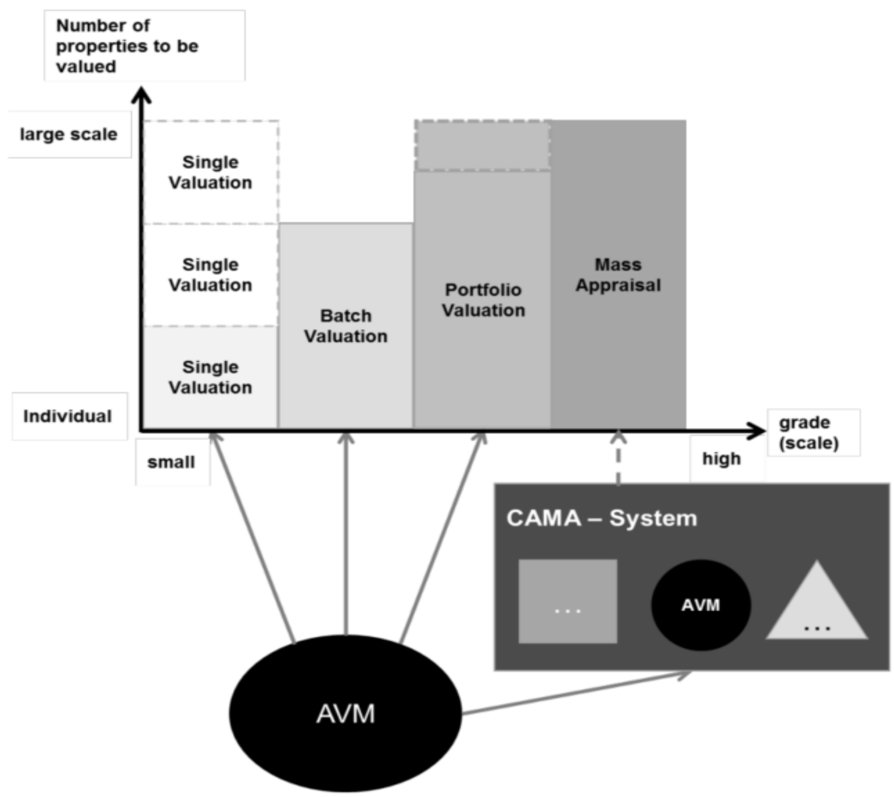

Figure 1: Comparison between AVM and CAMA

(Kindt & Metzner, 2017, p.9)

2.2 Automated Valuation Models: the advantages, the disadvantages, and the use

2.2.1 Application of AVMs

Although AVMs have become increasingly popular recently, applications of AVMs have been deployed over many decades. The early signs of AVMs originated in the 1960s and effectively deployed in public domain which mainly is rating and taxation assessment (Rossini & Kershaw, 2008). AVMs have been widely adopted especially in the United States with more than 50% of all identified AVM application are recorded (Metzner & Kindt, 2017, p. 30). However, the usage of AVMs has gone beyond North America, became increasingly mainstream in European countries since the 2008 global financial crisis took place following different purposes. For instance, in Germany, AVM is used in the banking industry. The shift derived from the need of lowering the cost and "rationalization the processes" In Norway, AVMs have been favored given that AVMs help increase transparency and "better risk management". In the Netherland and Italy, the main purposes are to improve quality control, manage risks and enhance loan-level data (European AVM Alliance, 2016). To date, there are twenty-six countries from five continents (i.e. Europe, North America, Oceania, Asia, and Africa) are applying AVMs in many domains (Metzner & Kindt, 2017, p. 29). Those are summarized in the table in the below.

Nr.	Continent	Country	Number of Appllication cases	% of total number of identified Application cases
1	Europe	Austria	2	2,6%
2		Czech Rep.	2	2,6%
3		Denmark	17	22,4%
4		Germany	15	19,7%
5		Great Britain	36	47,4%
6		Greece	3	3,9%
7		Ireland	4	5,3%
8		Italy	11	14,5%
9		Montenegro	3	3,9%
10		Netherlands	29	38,2%
11		Norway	16	21,1%
12		Poland	1	1,3%
13		Portugal	2	2,6%
14		Romania	4	5,3%
15		Spain	7	9,2%
16		Sweden	16	21,1%
17		Switzerland	20	26,3%
18	North America and Oceania	USA	43	56,6%
19		Canada	7	9,2%
20		New Zealand	10	13,2%
21		Australia	24	31,6%
22	Asia	China	2	2,6%
23		Japan	4	5,3%
24		Singapore	3	3,9%
25		Taiwan	4	5,3%
26	Africa	South Africa	8	10,5%

Table 2: Countries apply AVMs

(Mezner & Kindt, 2017, p. 29)

Switching from traditional use from the very first days (i.e. rating and taxation), AVMs now present in every core process of real estate management. The most popular application field is financing which mortgage lending (collateral risk assessment) and securitization are centers of focus (Metzner & Kindt, 2017). A brief AVM application use is illustrated in Figure 2.

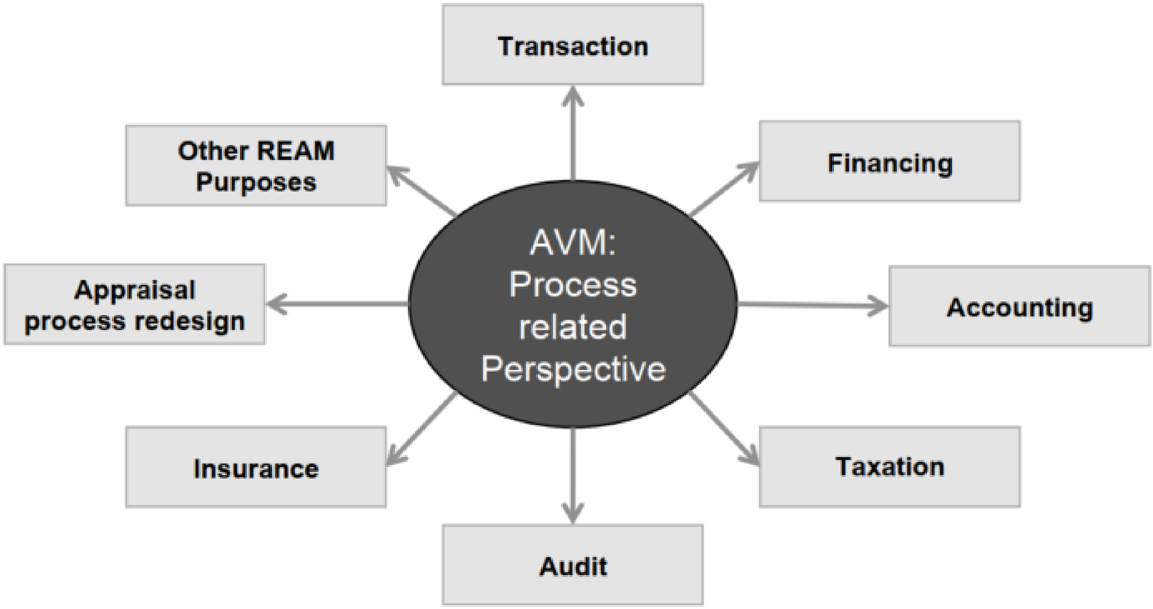

Figure 2: AVMs and its related application

(Metzner & Kindt, 2017, p. 18)

AVM could be seen as a revolution in real estate management due to the fact that its application uses help tackling with many kinds of problem. In credit decision purpose, lenders now can use AVMs as an alternative option to check whether the proposed value of a given collateral asset is acceptable with low cost first, before making further decisions and spending more money to order a full valuation by a human appraisal. In audit domain, lenders can use AVMs as secondary resources to double-check whether values derived from human valuers are accurate. AVM is also an effective tool in a way that it can assess both multiple properties and individual cases. In fraudulent detection domain, AVMs can evaluate many properties prices at a time and hence detect those do not follow the normal market trend at ease. Especially, AVM clearly shows its efficiency when doing mass valuation thanks to its time-saving and cost-effective advantages. Moreover, public authorities may really favor AVMs when calculating compensation payment for homeowners as expenses of new public work (i.e. road, highway, airport expansion, etc.). With a proper AVM, the likely cost could be delivered in a fast and cheap manner, and keep it up to date if necessary. Besides, investors could also leverage the use of AVMs in estimating expected tax capital for either single or portfolio properties for tax planning purpose. (d' Amato, 2017)

Currently, AVMs are mostly developed and have long-time of using in residential real estate market. The applications and detailed levels are quite mature in the residential sector because data and levels of granularity in the residential market are more homogenous and simple to resolve than from that of the commercial. Additionally, the housing data are more available and a number of transactions are more frequent in the aforementioned. For those reasons, AVMs in commercial real estate are still under research and development phase. Only a few research in commercial and hotel properties have been documented (Metzner & Kindt, 2017).

2.2.2 Automated valuation models: advantages and disadvantages

Since real estate accounts for one-third of the global wealth, and in fact, it is "the largest asset class in the world" (Kok, Koponen, & Martínez-Barbosa, 2017) the accuracy of property valuation has become important than ever when assessing those assets. The precision of real estate valuation has been a center of attention over decades to both academics and practitioners deriving from the fact that manual or traditional appraisal requires a lot of time and finance to assess property values. Although the real estate sector has encountered dramatic valuation cost, reported USD 90 billion per annum approximately (Kok, Koponen, & Martínez-Barbosa, 2017, p. 202), the appraisal results have not been so optimal. Cannon & Cole (2011) documented a standard a deviation of 12% averagely between the actual transaction and appraisal price for the US commercial property throughout the year 1984 - 2010 period using sell data from National Council of Real Estate Investment Fiduciaries (NCREIF). The deviation also varies significantly across countries and years, however, the main difference ranges between 7.7% and 13.9% according to MSCI research in 2016 (Kok, Koponen, & Martínez-Barbosa, 2017). Meanwhile, the rise of big data application, modeling techniques, mathematical algorithms, also computer computation are more and more increasingly adopted in many sectors. This leads to the need for leveraging those data and available tools to construct automated valuation models for real estate for the sake of automation, lowering the cost and time. A good AVM might take a significant time and skills to construct in the beginning phase, however, once it is ready in use, AVMs can help to speed the progress and reducing costs of valuation significantly. Valuers, therefore, would be able to know property prices with just "a-click-on-the-button".

Manual valuations or human valuations are conducted with physical property inspections and reviewing case by case. Those appraisals though effective, are subjective (Adair & Mcgreal, 1998), prone to human bias and errors (Benjamin, Guttery, & Sirmans, 2004). Moreover, because of their experience and cognitive bias, experienced appraisals often choose comparable sales in a smaller group and consider only property's key attributes than the less experienced ones (Diaz & Hansz, 2002). This although helps them speed up the valuation process, it may make them miss, for instance, an important demographic trend leading to wrong estimations (Diaz & Hansz, 2002). Diaz & Hansz (1997) also proved in their study that a given valuer is influenced by other's opinions when he or she is not familiar with the subject area. Furthermore, there is also evidence that client valuation feedback influences the valuation of the property (Diaz & Hansz, 2002). In response, valuers give valuations into expectations of large clients who often appear in the market as clients (Źróbek, et al., 2014).

AVMs, on the other hand, value property based on huge data as inputs without human interference, thereby eliminating the risk of bias and subjectivity. Speed, consistency, accuracy (Jahanshiri, Buyong, & Shariff, 2011), non-biased and inexpensive (Fortelny &

Reed, 2005) are well-known advantages of AVMs. Calhoun (2001) reasoned that AVM speeds up the valuation process because of lowering the need for manual review, exceptionally cases identified by AVM. The value estimation outputs produced by AVMs are not influenced by positive/negative judgment nor client's pressure, and hence less subject to bias (Fortelny & Reed, 2005). In addition, it is more cost-saving comparing to manual appraisal due to the fact that AVMs do not require many resources such as intensive employee's working hours, running a vehicle and office expenses (Fortelny & Reed, 2005). Tretton (2007) added to AVM's advantages that AVMs can be used both for mass appraisal and individual property. AVMs are clearly attractive when performing a large number of valuations e.g. mortgage valuations. Besides, AVMs enable more sophisticated risk management to mortgage business since it provides statistical results on time and could be easily integrated into qualitative risk management program of the lender (Downie & Robson, 2008). More importantly, the accuracy of AVM can be empirically tested on large samples, which make the valuation work more transparent (European AVM Alliance & European Mortgage Federation, 2016).

Apart from many benefits, AVMs also have tradeoffs. First, as a rule of thumb of modeling, AVMs requires a huge amount of comparable sales as inputs in the model developing process. Although data is prerequisite in constructing AVMs, a limited amount of data is generally available (Gilbertson & Preston, 2005). Quality of the data is also one of the concerns. As stated in (IAAO, 2003), quantitative data which can be measured like age, size is more objective. However, qualitative data is usually descriptive and subjective and hence requires the experience of the person collecting data. Secondly, an AVM does not require property inspections, and hence fail to examine the structure of the property. This aspect becomes critical when in many cases, a structure might account for most of the value of the property (Fortelny & Reed, 2005; Tretton, 2007). Gilbertson & Preston (2005) also added potential pitfalls of AVM in valuation are that AVM fails to detect misleading figures and correct them before they affect the value of other property, be capable for financial fraud, or even values predicted could be inaccurate. Besides, AVMs lack "street-level" judgment and intuition originated from a human valuer, which are necessary for interpreting market condition (Mooya, 2017).

2.3 AVMs development process

Since aiming to provide most likely property prices, AVMs must follow the important principles i.e. "transparent, provide a confidence level for the stakeholders, be broadly applicable and achieve statistically sufficient information" (IAAO, 2018, p. 4). Therefore, the construction of AVM consists of thorough certain phases in order to ensure the quality of models. As reported by IAAO (2018, p. 7) the process has nine steps in greater details, ranging from establishing the scope of work to finalizing the model. These are:

(1) *"Scope of work*

(2) Identification and acquisition of property data
(3) Exploratory data analysis
(4) Stratification
(5) Determination of data representativeness
(6) Model specification
(7) Model calibration
(8) Quality assurance
(9) Model application and value review" (IAAO, 2018, p. 7)

In line with that, Schulz, Wersing, & Werwatz (2014, p. 134) divided the AVM development process into four broader stages, including:

(1) "Establishing continuous access to reliable data;
(2) Model development and validation,
(3) Roll-out and service provision, and
(4) Backtesting."

Gloudemans & Almy (2011, pp. 266-268) listed eight primary steps in modeling, namely:

(1) "Data assembly
(2) Exploratory data analysis
(3) Base model
(4) Full model
(5) Sales ratio testing
(6) Model refinement
(7) Final model
(8) Model application"

On the whole, the AVM development process requires data acquisition and data quality check, data preprocessing before modeling, model specification and calibration, as well as model validation and application. These steps are explained in greater details in the below, following AVM standard of IAAO (2018).

First and foremost, the scope of work and property identification must be stated clearly in the beginning. Property identification is the process of identifying what kind of property is being appraised, for example finding maps, records or address that associate with a property. This step is relatively straightforward in developed countries (IAAO, 2003) since property record is well-documented. In IAAO (2018), valuer is also required to identify what type of property, market area that an AVM would cover, and assumptions that are used in AVMs. In practice, one of the most frequent assumptions is made in AVMs is the condition of the property because AVMs do not conduct any physical inspection of properties. Most AVMs assumes the property's condition is the highest and best use (IAAO, 2018; Matysiak, 2017; see also Downie & Robson, 2008).

Secondly, the data would be acquired. Like any traditional appraisal, the valuation accuracy highly depends on precise data (TEGoVA, 2016). IAAO (2018) divides data into three broad categories, namely, property data, locational data, and market data. Property data is attributes related to physical characteristics of the property itself (e.g. age, size, condition, etc.) Locational data is an area in which a property is located, taking into account demographics, traffics, access to amenities and so on. Market data concerns, for instance, sales, income, and replacement cost information. Moreover, in DiPasquale & Wheaton (1992), economic data also is believed to influence real estate market. Those factors affecting property price will be discussed further in Chapter 3. Property-specific transaction data could be acquired from public property records such as tax appraisal values from the county assessor, from banks during the mortgage underwriting process, and/or transaction prices from Real estate investment trust (REIT) (Schulz, Wersing, & Werwatz, 2014).

Data quality has always been a potential risk for data-driven models. The consequence of misleading, incomplete, or missing data could lead models to fail for prediction (TEGoVA, 2016). Therefore, exploratory data analysis needs to be performed in the third step. The ended goal of this step is to ensure the data is complete and consistent. For example, outlier or unusual observations are detected and removed out of the sample in order to maintain the representativeness of the data (IAAO, 2018; see also Gloudemans & Almy, 2011). Distribution of the data is explored in order to check the frequency of value-related variables. Moreover, valuers need to acquire more insights about the relationship between independent variables and property price, time trends, or discernable patterns which potentially influence the prices.

The next phase is the model stratification. This is the step where property data is grouped for modeling and analysis in order to maintain the homogeneity of the data. Properties could be grouped by use such as commercial or residential. Then it could be divided more into detailed groups based on geographic area, physical characteristics or value ranges. Stratification happens when values of property vary dramatically among groups, and there are enough observations in each group. Commercial properties, as stated in IAAO (2017) should be stratified by property type. That is to say, a separate model should be developed for office, retail, and industrial/warehouse property. As opposed to residential counterpart which is usually geographically stratified, commercial properties are often modeled in a wider coverage area, for instance, a model of a specific type might be sufficient in an entire metropolitan area (IAAO, 2003).

Fifth, data representativeness needs to be ensured by valuers. This step is to ensure that the sample data used in building AVMs is randomly selected and hence, represents the whole population so that AVMs can be used in production. A sample is representative if its distribution of property values is similar to that of the population (IAAO, 2003). However, since finding the distribution of the whole population is difficult, an alternative way to get a representative sample is to choose a sample that has all important "value-related property characteristic” (IAAO, 2003, p. 24). Moreover, the amount of transactions data or number of observations must be sufficient in order to ensure the quality of AVMs. In principle, the number of sales must be “at least five times”, or “fifteen times is desirable the number of independent variables” (IAAO, 2018, p. 10).

Further, valuers will perform model specification. Model specification, as defined in IAAO (2018), is a process of reviewing sample data in order to select the most appropriate valuation models that deliver the best possible results (see also in Gloudemans & Almy, 2011). The choice of valuation model in model specification depends on data analysis conducted in the previous step and existing appraisal theory. Three of the most common approach to model valuations are cost, sales comparison, and income which will be discussed in greater details in Chapter 3, section 3.1. After which, this step also includes choosing a mathematical format and selecting the appropriate variables to be used in models.

Model calibration is to find the coefficient of variables in the model and deciding which variables should be kept or removed. It is important to notice that coefficients not only are statistically significant but also they must be reasonably in line with real estate domain knowledge. Calibration techniques range from statistics-based methods like regression to geographic-weighted regression, to neural networks. Many AVMs today use statistics as a calibration technique. Among all, some of the primary measurement of overall model performance is coefficient of determination (R2), standard error of the estimate (SEE), coefficient of variation (COV), and average percent error. The combination and iteration between model specification and calibration is the key to AVM’s accuracy and reliability. (IAAO, 2018; Schulz, Wersing, & Werwatz, 2014; Gloudemans & Almy, 2011)

The second last step is the process in which AVM’s performance is tested by comparing the actual transaction price and predicted price (i.e. given by an AVM) (TEGoVA, 2016). This process will use sales data which is not used from the model calibration process (i.e. hold out sample or cross-validation) (IAAO, 2018; Schulz, Wersing, & Werwatz, 2014). Evaluating AVMs performance on a new test set data provides a clear overview of the accuracy of AVMs, and is needed to determine whether AVMs are ready in used or require further specification. A uniform method for comparing the accuracy of different AVMs is Forecast Standard Deviation (FSD) (US Patent No. 10/944,593, 2006) and is primary test statistics used at an international level (Rossini & Kershaw, 2008). FSD is defined as the standard deviation of error distributions from AVM’s predicted results. As opposed to traditional standard deviation uses the mean of a set of number as the center, FSD always uses 0 as its center (US Patent No. 10/944,593, 2006).

Finally, model application and value review: once all of the above-mentioned steps are done, the model could be applied for the same type of property in a defined area. These values should be reviewed frequently in order to maintain the up-to-date of AVMs. (IAAO, 2018)

AVMs development process step by step is provided in Figure 3.

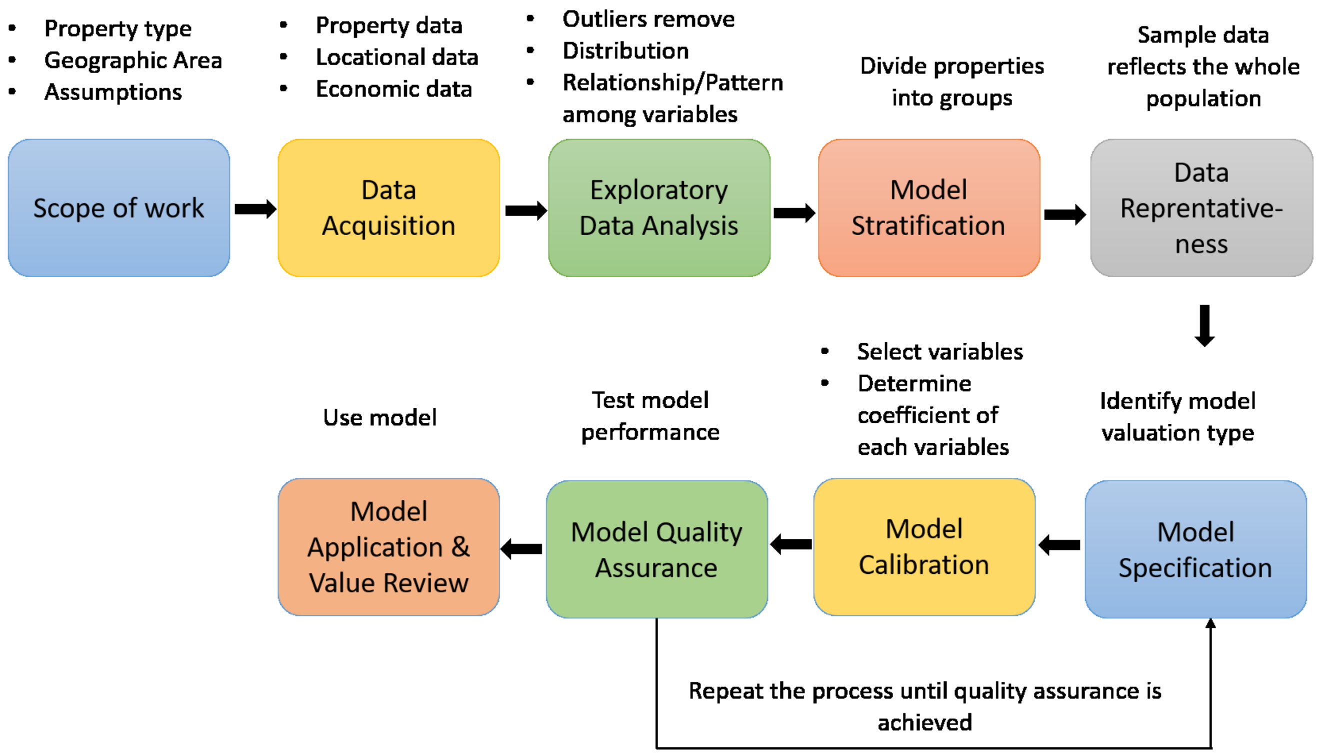

Figure 3: AVMs development process.

Source: Author summarized from IAAO (2003), IAAO (2017), and IAAO (2018)

2.4. Challenges of AVMs in commercial real estate

The accuracy of AVMs is highly dependent on the level of homogeneity of property types and the availability of transactions. Commercial properties, as a matter of fact, are more heterogeneous and irregularly traded in the market. For residential, the factors affecting the housing price are generally similar such as a number of rooms, size, and floors balcony. Thus residential property as stated in IAAO (2003) is commonly stratified into the market area to ensure the homogeneity. Commercial property, by contrast, is more heterogeneous, factors influence property prices vary from one type to another (which will be discussed further in Chapter 3). As a result, separate models are required for the different property type. Moreover, commercial properties are acquired for business/investment purpose thus require more funds and professional experiences from investors than residential, which explains why they are less frequently traded in the market. Consequently, data scarcity is one of the biggest challenges in AVM for commercial real estate. Furthermore, Gilbertson & Preston (2005) questioned whether AVMs could be fully used as official appraisal where valuation is completely produced by a computer program. The concern focused on the fact that valuation for commercial property requires both subjective and objective adjustment, and hence deserve more attention to verify the final valuation results (Boshoff & Kock, 2013). Another barrier when applying AVM in commercial real estate is that the nature of the local market. For those markets are inefficient or immature, it is difficult or even impossible to develop AVMs. According to Mooya (2017), small market size, transparency problem, weak property rights, and poor regulation are major barriers which lessen the applications of AVMs in those countries. The use of AVMs is heavily dependent on the nature of the local markets thus limits its broad applications globally (Mooya, 2017).

Chapter 3: Determinants of commercial property values

3.1 Real estate valuation method

There are three valuation approaches including cost approach, income approach, and sales comparison approach. For income-producing property like the case of commercial property, income and sales comparison are preferable (IAAO, 2017).

3.1.1 Sales-comparison approach

Sales-comparison is based on the assumption that value of a property in question could be estimated based on similar properties that have been recently transacted in the market (IAAO, 2003). Lawson (2008) in his literature's citation stated that sales-comparison approach is drawn on two main assumptions. Firstly, market price is an evidence of market value, hence is seen as market value; and secondly, substitutional properties that are used as comparables must have similar price range (Lawson, 2008). This means that the market is sufficient regarding both participants and transactions. In principle, when applying sales comparable approach, RICS (2012) prefers a greater number of transactions to a single transaction. The more similar those comparables are, the better results the appraisals have. In addition, comparables should be recently transacted so that these can represent current market trend (RICS, 2012).

According to IAAO (2018), the sales-comparison approach can be divided into (1) comparable sales model or as a (2) direct market model. Kummerow (2003, pp. 2-3) describes a chronological process of property valuation using sales-comparison approach as follows;

a) *"Choosing which sales are best to use to infer price*
b) *Identifying price-affecting characteristics that differ between sales and the subject property*
c) *Estimating the dollar value of the differences for each pair-wise comparison of the subject sale*
d) *"Reconciling" to give a single price estimate, where indicated values of the subject from different adjusted comparable sales are not identical."*

The chronological process in the above could be summarized as a formula for comparable sales model in (IAAO, 2003, p. 9 cited in Gloudemans, 1999) as follows;

$$MVs = SP_c + ADJ_c$$

Where MVs = market value estimate;

SP_c = selling price of a comparable sale property; and

ADJ_c = adjustments to the comparable sale.

Regarding direct market models using Sales comparison approach, has a form of regression analysis, may take one of the three model structures:

• *Additive (also termed "linear"),*

• *Multiplicative (also termed "log linear"), or*

• *Hybrid (also termed "nonlinear")* (IAAO, 2018, p. 22)

<u>Additive model</u>

Additive models are easiest to calibrate and interpret results, hence they are the most frequently used in AVMs. Additive models have the form:

$$MV = B0 + B1 \times X1 + B2 \times X2 + ...$$

Where *MV is the dependent variable;*

B0 is a constant;

Xi represents the independent variables in the model; and

Bi are corresponding rates or coefficients (IAAO, 2018, p. 22)

MV is the market value or sales price of a property

<u>Multiplicative models</u>

$$MV = B_0 \ x \ X_1^{B1} \ x \ X_2^{B2} \ x...$$

Where *MV is the dependent variable;*

B0 is a constant;

X_1^{B1} where X represents the independent variables in the model; and

X_1^{B1} where B1 represents the corresponding rates or coefficients. (IAAO, 2018, p. 23)

In this example, each variable is raised to a corresponding power.

Multiplicative models have several advantages such as they are able to capture the curvilinear relationship and also adjust proportionately to the value of the property in question (IAAO, 2018), especially if there is nonlinearity relationship among observations. In addition, because multiplicative models require logarithmic data transformation, the variation between independent variables is narrowed down. As a result, more equal weight is given to each property and the impact of outliers is decreased. (Gloudemans R. J., 2002)

Hybrid (Nonlinear) models

Hybrid (nonlinear) models combine additive and multiplicative models, therefore have advantages from these two. The following example of a hybrid model is a model specification that separates value into building, land, and "other" components (e.g., outbuildings):

$$MV = \pi GQ \times [(\pi BQ \times \sum BA) + (\pi LQ \times \sum LA) + \sum OA]$$

Where

MV is the estimated market value;

πGQ is the product of general qualitative variables;

πBQ is the product of building qualitative variables;

ΣBA is the sum of building additive variables;

πLQ is the product of land qualitative variables;

ΣLA is the sum of land additive variables; and

ΣOA is the sum of other additive variables. (IAAO, 2018, p. 23)

3.1.2 Income approach

The income approach is the most interesting method for income-producing properties. Gylling (2006) explained it is because when investing in one asset, investors mainly focus on the aspect that how much incomes his assets could generate during the holding period. As a result, this is the most appealing method for estimate values of income-producing property. There are two methods derived from the income approach, namely, direct capitalization method and discounted cash flows method (DCF).

3.1.2.1 Capitalized NOI/capitalization method

The most common used method in property valuation is to divide the stabilized net operating income (NOI) by capitalization rate (cap rate).

*Value of a property = Stabilized NOI / Cap rate (*Glickman, 2014, p. 129)

This above-mentioned formula is a form of perpetuity calculation assuming that a given property will generate a stabilized net operating income forever. It is vital to notice that NOI, in reality, varies year by year (actual NOI) given that rental incomes and expense will change along with different time. Stabilized NOI, however, is a concept indicating a measurement of long-term performance of a property (Glickman, 2014). Therefore, stabilized NOI assumed to be constant (Glickman, 2014).

Cap rate or yield is a ratio measuring income in relation to price of an asset (Geltner, Miller, Clayton, & Eichholtz, 2001). Real estate is an asset class, and hence it needs to compete with other alternative asset class like stock and bonds for investor capital. As such, cap rate is determined by economic conditions and financial market. The common way to derive cap rate is to compare cap rates of recent comparable transactions. The most relevant criteria when choosing sales comparables are quality, size, use and market segment. (Glickman, 2014)

The capitalization approach is attractive thanks to its simplicity, easy interpretation, and quick calculation. However, this method requires subjective assumptions about NOI and it is challenging to measure the cap rate of a sold property due to the difficulty of measuring operating expense.

3.1.2.2 Discounted cash flows (DCF) method

The DCF model calculates a market value of a property by summing the future cash flows during a holding period and its terminal value assuming that property owner would sell it at the end of the investment. The cash flows are discounted back to the current day at the discount rate. This is a method used to convert future benefits, including scheduled incomes and property terminal value, into present value by discounting future cash flows back to the current date (Sevelka, 2004)

The discount rate reflects the value of money over time and a risk premium, "representing compensation for the risk inherent in future cash flows that are uncertain" (RICS, 2010, p. 6). Cash flows are estimated based on predictions of leasing information including rent reviews, lease renewal on expiry lease, and void costs if part of the property is vacant. The terminal value is forecasted as a result of forecasted rental growth, unexpired leases at the exit date along with exit yield. Yield is tied with property-specific factor and equilibrium market conditions.

Deterministic variables and descriptions (Brueggeman & Fisher, 2008, Chapter 10, pp. 280-318; see also Brown, 2005, Chapter 4, pp. 73-98) are listed in the below:

- Potential Gross Income (PGI): total annual income derived from a property given that it is fully leased
- Income growth: the amount of which total annual income increases per year. This is forecasted based on either rent review tied to specific lease term contract (if any) or typically, cost of living index.
- Vacancy: the amount of income loss when the whole or partial property is vacant throughout the period
- Effective Gross Income (EGI): the annual income after taking into account vacancy
- OPEX: annual operating expenditure estimation
- Net Operating Income (NOI): the annual actual income after excluding vacancy and OPEX
- CAPEX: capital expenditure estimation per year
- Pre-tax cash flows: the annual actual income after excluding CAPEX
- Terminate Value (TV): the value estimation of property at the end of the holding period
- Discount rate: the rate at which future cash flows are discounted to the current date.
- Present Value (PV) (or market value estimation): the sum of future cash flows after discounted back to the current time. The formula for PV is defined as:

$$PV = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t}$$

Where PV = present (market) value;

C_t = forecasted incremental cash flow after corporate tax – strictly speaking, the mean of the distribution of possible $\tilde{C}$'s;

T = project life (Ct includes any salvage value);

r = the opportunity cost of capital defined as the equilibrium expected rate of return on securities equivalent in risk in the project being valued. (Myers, 1984, p. 127)

Table 3 provides information that is needed for discounted cash flows model.

Type of information	Current data	Forecasts
Tenure	• Title, including headlease details (if applicable) • Outgoings • Head rents • Unfulfilled statutory obligations	
Physical attributes	• Floor areas (net and gross) • Ancillary areas and car parking • Building specifications • Tenants' improvements	• Planned or possible changes in areas/ parking provision
Lease/sublease and occupational interests	• Tenancy details • Lease expiry dates • Break clauses • Rent review dates • Rent review terms	• Lease events forecasts, including probability of breaks being operated and leases renewed • Duration of future voids • Perpetual void allowance
Rental value	• Rents passing (including stepped rents) • Estimated rental values	• Growth in rental value for the location to model refurbishment/ redevelopment options • Growth in actual property rents
Costs of property ownership and holding costs	• Vacancy/void costs • Unrecoverable service costs • Unrecoverable management costs • Letting and review costs • Purchase and sale costs	• Inflation in maintenance and running costs • Future periods on lease expiry and periods of refurbishment
Redevelopment/ refurbishment	• Costs of redevelopment/ refurbishment • Dilapidations	• Inflation in building costs
Finance	• Loan details • Break costs	• Changes in interest rates
Gearing	• Level of debt • Return on equity employed	
Taxation	• Income and capital gains • VAT election • Capital allowances	

Table 3: Information needed for preparation of DCF

(RICS, 2010, p. 4)

Discounted cash flows model requires many assumptions need to be made since it forecasts property incomes generated in the future. The three most important components are (1) annual cash flows during the investment term, (2) terminal value, (3) and discount rate because only slight adjustments in these three could cause to considerate change in values estimation (Glickman, 2014).

Annual cash flows

Although cash flows could belong to the whole or partial asset, cash flows of the whole asset are typically selected. Cash flows could also be pre-tax or post-tax (IVSC, 2017). However, in assessing market value, tax is not usually considered into calculation since comparables usually analyze rentals and expenditures gross of tax (RICS, 2010). The forecast cash flows periods are normally between five and ten years (Wyatt, 2013, pp. 115-160). Nonetheless, the shorter the forecast period, the higher impact of terminal value and transaction cost upon the value estimation (RICS, 2010). IVSC(2017, p. 40) notes the projected cash flows document both inflows and outflows derived from a property in question, and should reflect one of those things:

(a)" Contractual or promised cash flow

(b) The single most likely set of cash flow

(c) The probability-weighted expected cash flow, or

(d) Multiple scenarios of possible future cash flow."

Discount rate:

There are more than one ways for valuers to derive an appropriate discount rate. All common methods, according to IVSC (2017, p. 42), used to derive discount rate are:

"(a) the capital asset pricing model (CAPM),

(b) the weighted average cost of capital (WACC),

(c) the observed or inferred rates/yields,

(d) the internal rate of return (IRR),

(e) the weighted average return on assets (WARA), and

(f) the build-up method (generally used only in the absence of market inputs)"

The discount rate must compensate for the risk which an investor is willing to take over the investment. Typically, discount rate equals to risk-free rate of the alternative riskless asset (for instance government bonds) plus additional risk (RICS, 2010). While estimating of risk-free rate is clear and straight forward, identify additional risk is more complicated. Risk-free is commonly measured by 10-year Treasury bond or inflation rate and typically fixed for any kind of property investment. Additional risk includes market risk premium (or systematic risk). Although market risk premium (or systematic risk) is rewarded since unique risk (i.e. the risk that associates with the asset) could be removed by diversification (Sharpe, 1964; Lintner, 1965), the actual performance of property assets has huge variations given that heterogeneity of the asset class. As a result, unique risks in commercial real estate are more often matter. Therefore, valuers may choose to add unique risk in addition to market premium risk and risk-free rate in order to derive discount rate. (RICS, 2010)

Other ways to derive discount rate could be,

"(a) A single discount rate for all property investments,

(b) A discount rate for each class of property – either by use (offices, shops, etc.), subtype (unit shops, shopping centres, etc.) and/or location,

(c) A discount rate reflecting the risks of a specific property cash flow

(d) Different discount rates applied to different components of the cash flow according to their risk – for example the passing contractual rent until lease expiry (risk dependent on known tenant covenant), reversionary rent at future rent reviews (risk dependent on known tenant covenant and market rental change) and rental income beyond lease expiry (risk dependent on unknown tenant covenant and market rental change)" (RICS, 2010, p. 10)

Method (c) is highly time-consuming regarding specific research for each cash flow over investment periods and sometimes could be impractical given that poor quality of individual property data and infectiveness of real estate market as a whole. Method (a) uses a single discount rate for all property investment, distinguishing only type of investment class such as bond or stock assuming. Consequently, this method ignores different levels of sector-specific risks among submarkets for instance retail versus office, city center versus countryside which could lead to underestimate or overstate risks. Therefore, method (b) and method (d) would be a better approach. (RICS, 2010)

Terminal value:

The terminal value or residual value is value of property or re-sale price at the end of the investment. This value should reflect the physical state of the property and values of lease at the exit date (RICS, 2010). There are many ways to estimate the terminal value. However, the most common way in DCF is to assume that net cash flows of the last year of the holding period is to grow constantly. Terminal value (TV) equals to:

$$Terminal\ value_t = \frac{Forecasted\ Cash\ Flow\ t+1}{r - stable\ growth}$$

(Domodaran, 2002, p. 306)

In addition, valuers could also adjust yield with additional risk to derive exit yield. Wyatt (2013) and Brueggeman & Fisher (2008) show a common assumption in real estate valuation regarding estimating the terminal value that exit yield (going-out cap rate) is higher than yield (going-in cap rate). This is because real estate market is believed to be, or will eventually reach equilibrium. Meanwhile, properties along with time depreciate and become obsolescent. NOI of an older property will be less than that of new ones. When every other factor is constant, the difference between yield and exit yield reflects economic depreciation (Brueggeman & Fisher, 2008).

It is also important to notice that terminal value could be a site value if the demolition of the property is forecasted. It could also be zero if the cash flows duration occurs with lease expiry (RICS, 2010).

3.1.3 Cost approach

The cost approach is based on an assumption that land where a building is located on is vacant and unimproved, and the subject property does not exist yet (Gylling, 2006). The property value, hence, is calculated based on the construction cost to build a new similar property from scratch (i.e. replacement cost), deduct any depreciation value, and plus the value of land.

IAAO (2018) stated this approach is an indirect method of estimating market value. The cost approach is suitable with special properties, newly built properties and properties with insufficient sales. Especially, properties are located in the suburban area with vacant land exits are easier to use this approach since it is possible to know land values, and cost of construction a new equivalent building. The formulas for calculating property values based on cost approach is as follows;

$$MV = \pi GQ \times [(1 - BQD) \times RCN + LV]$$

Where:

MV is the market value;

πGQ is general qualitative variables such as location, economic adjustments, and time of sale;

BQD is a building qualitative variable representing depreciation;

RCN is the replacement/reproduction cost new;

LV is the land value. (IAAO, 2018, p. 21)

And

$$MV = \pi GQ \times [(\pi BQ \times \sum BA) + (\pi LQ \times \sum LA) + \sum OA]$$

Where:

MV is the market value;

πGQ is product of general qualitative variables;

πBQ is the product of building qualitative variables;

ΣBA is the sum of building additive variables;

πLQ is the product of land qualitative variables;

ΣLA is the sum of land additive variables; and

ΣOA is the sum of other additive variables (IAAO, 2018, pp. 21-22)

It is also important to notice that the cost tables provided by a third party must be adjusted in accordance with local market practice and the way the unit-in-place costs were aggregated before constructing AVMs. (IAAO, 2018)

The advantages and disadvantages of each approach is summarized in the below:

Approach	Advantages	Disadvantages
Sales comparison	● Reflect the supply and demand at the equilibrium price ● Appraisal price derived from the actual prices of similar transactions	● Real estate market is decentralized and hence, information is not published fully and widely ● Not applicable for special properties or properties with insufficient sales
Income	● Reflects the ability of generating cash flows derived	● Based on a lot of assumptions and prediction in the future

	from properties ● Suitable with income-producing properties	● Determine cap rate and discount rate is difficult
Cost	● Suitable for special properties or properties without sufficient transactions	● Value of land is not always available ● It is hard to estimate cost of replacement of old properties (e.g. building were built 30 years ago etc.)

Table 4: Advantages and disadvantages of different valuation approaches

3.2 Factors that Influence the Values of Properties

It is generally accepted, property values are determined by economic, location and property factors (Kim and Brand, 2015). This is in line with many previous studies before. For example, Beekmans, et al. (2014) summarized results from previous researches then concluded that property characteristics are the most important explanation for the property prices, and hence, should be placed at the core of property values' constitution. The second factor is the location where properties are situated. Finally, the financial and macroeconomic factors including regional and national conditions act as a broad context, also contribute to changes in real estate market (DiPasquale & Wheaton, 1992). The factors affect property prices are illustrated in the figure in the below.

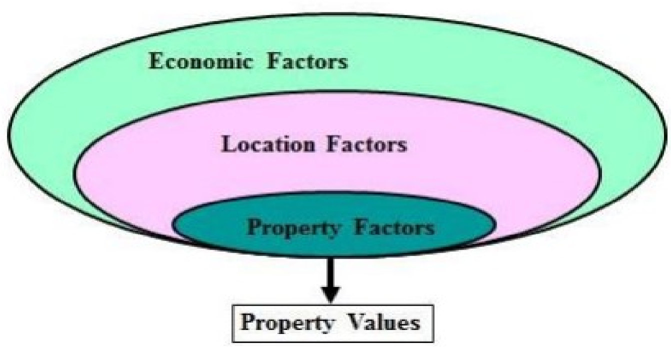

Figure 4: Conceptual Framework of Property Values

(Kim & Brand, 2015)

3.2.1 Economic factors

As presented in the analytic framework illustrated by four-quadrant diagram (DiPasquale & Wheaton, 1992), real estate market is clearly influenced by national economy and financial market. In line with that, Naranjo & Ling (1997) proved the usefulness of economic data in predictability of real estate returns. Kim and Brand‘s 2015 study (as cited from Boykin & Ring, 1993) addressed that the property market, like other asset markets such as stocks and bonds, is directly influenced by the general economic condition of the country. The important economic indicators, for instances, Gross Domestic Product (GDP), interest rate, unemployment rate, inflation rate, and new building constructions.

The economic factors are divided into two groups based on their impacts on the demand and supply side. On the demand side, economic factors are such as population or number of household, total community income and distribution, employment, and interest rate (Kim and Brand, 2015, cited from Barrett & Blair, 1988; see also DiPasquale & Wheaton, 1992). The new supply side is determined by the price of assets in relation to the cost of constructing them, and rental and sales price patterns of current properties (DiPasquale & Wheaton, 1992; Kauko, Lorenz, Dent, Lützkendorf, & Hill, 2017).

Noticeably, interest rate has an important role in property market dynamics regarding both supply and demand side, resulting in changes in property prices. A negative relationship between commercial real estate and the interest rate has long been hypothesized (DiPasquale & Wheaton, 1992). The reason is that property market activities for instances occupation, investment, and development are influenced heavily by changes in interest rate. A rise in interest rate usually causes a decrease in economic growth leading to a reduction in economic activities, and hence the occupational demand among enterprises in the property market is slowed down. At the same time, higher interest rates also increase the costs of development i.e. supply side since most developers borrow finance to develop properties. As a result, the interest rate is an essential indicator to analyze property prices. (Kim and Brand, 2015)

3.2.2 Location factors

Since property’s characteristics are immobility and longevity, the surrounding area where a property is located contributes to values significantly. The influence of location factors on property values have been long been researched in many studies such as Waddell, Berry, & Hoch (1993), Mahan, Polasky, & Adams (2000), Tse & & Love (2000), and Tse & Chan (2003). Current values of properties are projected based on their future incomes and capital growth. Therefore, if the economic activities of one region fail, the values of properties within that region also decrease even though there is no change in the economy at the national level (Kim and Brand, 2015). It is because market participants have a pessimistic view about the property’s value potential growth. The development of new properties i.e. supply side also slows down causing changes in equilibrium.

Most of the studies see location factors as directly related to property in question. Location factors could be examined by accessibility and centrality. Accessibility is an effective way to measure the goodness of one location that is measured by time and cost to travel to other locations (Tse & & Love, 2000). Centrality is drawn from the theory of Economies of agglomeration (Beekmans, Beckers, Krabben, & Martens, 2014) which is related closely to economies of scale and network effects. This means that a firm prefers to locate near to similar businesses because of the reduction in cost and attracting more customers and suppliers. As a result, property values increase if it is located close to other similar properties since occupational demand for this property is high.

Location factors could be good social neighborhood amenity, zoning, ground conditions and topography, availability of transport, convenience of transport, parking, environmental impact, impact on government services, distance to city central business district (Kim and Brand, 2015, cited from Barrett and Blair, 1988; see also So, Tse, & Ganesan, 1997 and Tse & & Love, 2000)

3.2.3 Property factors

Property physical characteristics are the most explanatory factors for the prices. It is apparent to accept that the purpose of use of property determines what physical characteristics that are required to have in the property under research. However, there are certain factors that play a major role in property values regardless of their purpose of use. Firstly though not surprisingly, the size of the property is one of the most important factors constituting the property price (Beekmans, Beckers, Krabben, & Martens, 2014). Hartzell, Hekman, & Miles (1986) explained larger buildings tend to generate more returns because of two reasons. Firstly, larger buildings bring more rental incomes while requiring fewer management efforts per rental income. Secondly, larger buildings may offer more diversified tenants, therefore maximizing rental incomes and reducing the tenant risks. However, increasing the size of the property does not increase the value of property forever (Monson, 2009). At a certain level, the size of the property will not affect the property price anymore.

The second important factor is age, or year built, of property under research (Beekmans, Beckers, Krabben, & Martens, 2014) since buyers often prefer the newer to the older. Though old properties could be renovated, as a matter of the fact, newer ones contain more amenities that buyers nowadays are seeking and thus are more desired in the eyes of buyers. Moreover, a renovation year is also important for determining property prices because it reflects the quality of the building. Apparently, buildings with a recent renovation will have better conditions than the old ones assuming those were built at around the same time.

Another important variable that an analyst has to consider in AVMs is that the date of transaction/appraisal. Real estate market is subjected to the economy (Renigier-Bilozor & Wisniewski, 2017), therefore, it is necessary that this variable is included in AVMs.

These sections in the below analyze deeper into details what kind of building characteristics that analysts need to consider in AVMs upon different types of property, and how those related to properties price.

3.3 Office property

The office market can be classified based on many criteria, for instance, location (i.e. CBD, suburban) and intensity (i.e. high rise and low rise). Within each of these categories, office buildings can be ranging from generic usage type to highly specialized type. Within each building categories, the office could be more segmented based on the design structure, layout, and materials and so on (DeLisle, 2019). That information, although important and useful, usually are not widely available. Consequently, analysts should select most important factors inputs which possible to obtain that have a strong correlation and highly needed in predicting property prices.

Firstly, drivers of office values in AVMs could be drawn from the general economic condition by assessing the demand and supply of the market. Transaction date, hence, is significantly important in AVMs since it ties down the property value with the market cycle. Besides, there are two types of business affecting directly to the demand for office space. Those are Finance and Insurance, and Professional and Business Services. This is because businesses in these sectors involve financial transactions, development, and transfer of ownership of financial assets including real estate. Hence, growth or reduction in these businesses has a direct influence on real estate market and values of properties (DeLisle, 2019). Moreover, Lin (2012) summarized other economic indicators affecting to office property prices including (1) money supply, interest rate, GDP, white-collar employment, and (2) inflation and new office construction. While the former measures the growth rate of the economy, the latter measures the potential operating cost and stock supply. Besides, DeLisle (2019) added quality of life, education and population growth, Shilling (2002) added expanding local economy as indicators measuring the business attractiveness of the market. In addition, cap rates to interest rates and rental costs to mortgage costs are also important to measure the property values (Lin, 2012).

Location factors could be assessed by accessibility and centrality of a given property. The main indicators for accessibility are measured by how convenient it is to reach the city center, workplace, hospital, shopping and also municipal services (Türkoğlu, 1997; Shilling, 2002). Office properties with good access will have higher values due to their attractiveness and high satisfaction of tenants. Accessibility could be measured by a walking distance to the nearest public transport station (e.g. bus, train, or metro station) as well as driving distances to the nearest airport, highway entrance, city center (Kurzrock, Rottke, & Schiereck, 2011). Centrality could be assessed by the presences of restaurants, theaters, and shops or urbanization rate when information about given amenities could not be obtained (Beekmans, Beckers, Krabben, & Martens, 2014). Population density at a regional level could be a good indicator implying the urbanization and its potential growth rate.

At the building level, property factors could include variables in AVMs specification as follows:

- Primary property type of use: assess common use of property whether the property is highly specialized for special tenant's purposes.
- Total size of the property
- Green building (Energy Star or LEED certified): this factor is important since energy consumption accounts for a major part in operating expense within an office property, and hence affects to incomes, returns, and values of office properties;
- Floor area;
- Parking
- Stories
- Year built: measures the age of office properties. It is important since it represents the depreciation cost;
- Year renovated (if any): it is important since newly renovated building may satisfy tenants better than ones without. (Monson, 2009)
- For office property for letting and investment purpose, rent roll level, lease type, vacancy rate and a number of tenants are also needed to be considered since those influence to rental income and thus, property values at the end. (RICS, 2012)

Factors that needed to be examined for office properties in AVMs are summarized in the table in the below;

Office - property value determinants		
Economic factor	Location factor	Property factor
• Number of employee/ employment rate in Finance and Insurance industry/and Professional and Business Services. Money supply	• Distance to CBD • Distance to nearest public station • Distance to nearest highway • Distance to nearest airport • Presence of amenities (shops,	• Type • Transaction date • Total size • Floor area • Green building • Parking ratio • Year Built (age) • Year Renovated • Rent roll

• Interest rate • GDP • White collar employment • Inflation • New office construction (office) • Cap rates to interest rates • Rental costs to mortgage costs	restaurants, etc.) • Region • Population density/growth • Urbanization rate	• Lease contract type • Type of tenant • Vacancy rate

Table 5: Office - property value determinants

Source: Author summarized and aggregated from Gloudemans & Almy (2011), Lin (2012); Beekmans, Beckers, Krabben, & Martens (2014); Monson (2009); RICS (2012); Shilling (2002), and DeLisle (2019)

3.4 Industrial property

Regarding function, industrial property could be divided into mainly three types, including warehouse/distribution centers, hybrid facilities, and manufacturing facilities. While the first two types draw investors a huge interest, manufacturing facilities are mainly owner-occupiers. This is because this type of property usually requires some customizations in order to be suitable for the nature of the business, as well as some of the environmental issues could raise the risks of investment. Warehouse and distribution centers are different in their activities which they house rather than the structure of building designs. (DeLisle, 2019)

The demand for industrial property is driven heavily by commercial and industrial activity (Shilling, 2002). In addition, Lin (2012 believed that global and domestic economic conditions, business and consumer sales have big impacts on industrial property demand. Similarly to office property, money supply, interest rate, and GDP are indicators to measure the general economic conditions. Finally and similarly to office property in the section above, cap rates to interest rates and rental costs to mortgage cost could reflect the value of the industrial property.

At the location level, nearness to the major transportation routes is especially important for industrial property because those properties need to be able to obtain and distribute goods in a very effective cost and time-saving manner. In general, distance to the airport, distance to the harbor, and distance to the railway, the closer properties are, the higher values those have. The relation between property location and local amenities (i.e. measured by distance to CBD), opposed to office property, is not always straightforward. The probable reason for that is the location far away from local amenities might bring better accessibilities. Beekmans, Beckers, Krabben, & Martens, (2014) cited from Dunse and Jones (2005a, 2005b) said that there was a negative correlation between industrial rent and distance from the nearest large town. In Beekmans, Beckers, Krabben, & Martens (2014) 's study, they also drew the same conclusion.

At the building level, those internal factors need to be considered in order to value industry property in AVMs.

- Type of industrial properties: apparently, there are many types of property falling under this name. At the generic level, industrial could be divided into three main types, namely, manufacturing, warehouse/distribution, and hybrid facilities. This, however, could be categorized more into specific details depending on how detaileds the dataset which analysts have in model specifications. Industrial property classification in more details is illustrated in the below;

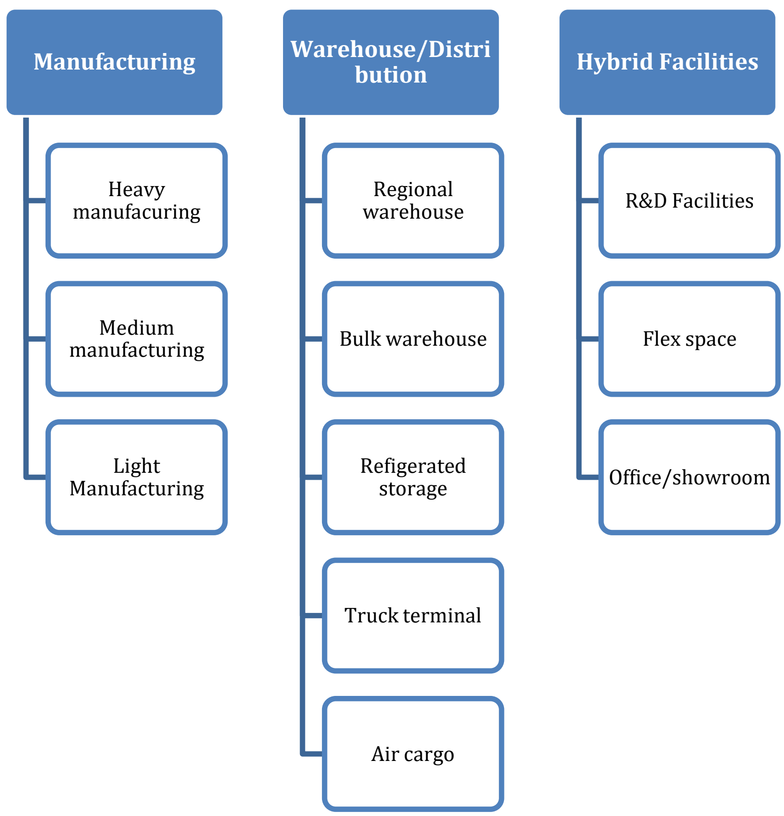

Figure 5: Industrial property type

Source: DeLisle (2019, p. 209)

- Land area

- Topography: Industrial users normally prefer level land since heavy timber, rock outcrops, landfill, and rock sub-strata land requires more efforts and money to develop or redevelop a site;
- Zoning: since different zoning allow different purpose of uses so it is worth to include it in AVMs;
- Year built (Age): represent for depreciation cost;
- Year renovated;
- Total size;
- Floor area;
- Building layout and height;
- Number and size of loading docks and bays: this indicates better assessment to properties via entry points for loading and unloading purpose;
- The ratio of office space to total space: this could range between 10–15% of the total floor space area for merchandising and light manufacturing and sometimes could exceed 50% for 'high tech' industries due to computer installation. (Monson, 2009: NSW DET, 2006)
- Industrial property for renting purpose, similar to renting an office, rent roll level, lease type, vacancy rate (RICS, 2012) are also needed to be considered. In addition, the industry in which tenant operates is also needed since it reflects the need for space

The factors that needed to be examined for office properties in AVMs are summarized in the table as follows;

Industrial- property value determinants		
Economic factor	Location factor	Property factor
• Money supply • Interest rate • GDP • Inflation • Industrial production • Manufacturing employment • Transportation employment • Airfreight volume • Rail and truck	• Distance to CBD • Distance to nearest public station • Distance to nearest highway • Distance to nearest airport • Region • Population density/growth	• Type • Transaction date • Land area • Topography • Zoning • Year built (age) • Year renovated • Total size • Floor area • Building layout and height

volume • Retail sales • Industrial capacity utilization • Cap rates to interest rate • Rental cost to mortgage cost	• Urbanization rate	• Number and size of loading docks and bays • Ratio of office space to total space • Rent roll • Lease contract type • Type of tenant • Vacancy rate

Table 6: Industrial- property value determinants

Source: Author summarized and aggregated from Gloudemans & Almy (2011), Lin (2012); Beekmans, Beckers, Krabben, & Martens (2014); Monson (2009); RICS (2012); Shilling (2002), and DeLisle (2019)

3.5 Retail property

Retail property is a very broad term referring to many different types of properties, ranging from street retail shops to mega-malls. Consequently, attributes associated with retail property values are complicated and extremely varied with a range of sizes, locations, and types.

A snapshot for retail property market structure and trends are illustrated in the figure as follows;

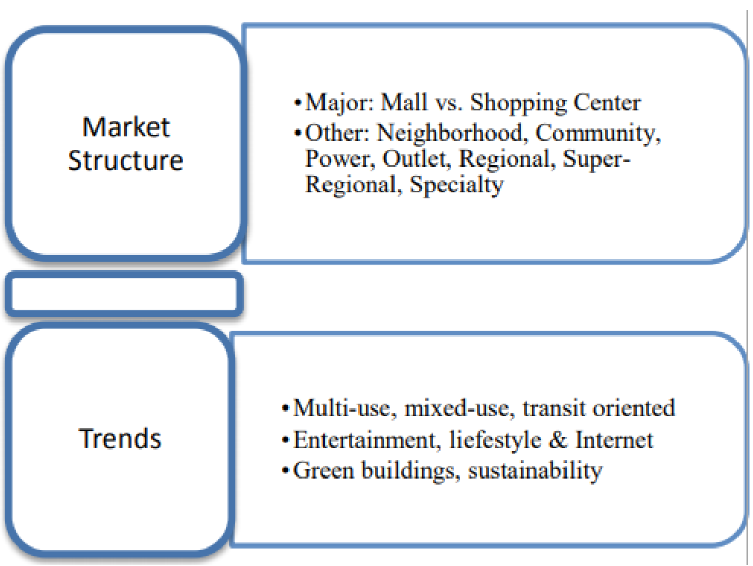

Figure 6: Retail property market structure

Source: DeLisle (2019, p. 268)

Retail property demand is driven by primary demands from tenants who lease premises, and secondary demand from consumers who visit retail premises (DeLisle, 2019). As a result, this source of demands is driven by economic conditions (DeLisle, 2019). These factors could be measured by general economic indicators such as money supply, interest rate, retail sales, inflation, car registration, retail sector expenditure, aggregate household wealth. Similarly to the office and industrial properties, retails is also subjected to vacancy rates, cap rates to interest rates, and rental costs to mortgage costs (Lin, 2012).

The location factors play a major role in property values due to the fact that its function is to serve consumers. Therefore, the easier accessibility is, the higher values retail properties have. Distance to CBD and distance to nearest public transportation are vital in AVMs. Moreover, population density where retail locates is needed to since its measures the chance that consumers will likely visit the retail. Centrality, similarly to office property, could be assessed by the presences of restaurants, theaters, and shops or urbanization rate. Population density at a regional level could be a good indicator implying the urbanization and its potential growth rate.

At the building level, some common factors as similar to office and industry are following;

- Total size;
- Floor area;
- Year built;
- Year renovated;
- Parking
- Stories;
- For center retail: shop frontage and display windows, and pedestrian flow should be reviewed;
- For retail is in out of town, building layout, height, and visibility should be reviewed.
- Lease term information is highly important in retail since those type of premises usually have diversified tenants leading to more efforts of managing tenants and operating expenses. As such, cash flows is exposed to higher risks. Therefore, rental level, lease terms, number of tenants, rental levels needed to be taken into account.

Those factors affecting retail property values could be summarized as follows;

Retail - property value determinants		
Economic factor	Location factor	Property factor
• Money supply • Interest rate • GDP • Inflation • Retail sales • Car registration • Retail sector expenditure • Aggregate household wealth • Cap rates to interest rate • Rental cost to mortgage cost	• Distance to CBD • Distance to nearest public station • Distance to nearest highway • Distance to nearest airport • Region • Population density/growth • Urbanization rate	• Type • Transaction date • Total size • Floor area • Year built (age) • Year renovated • Total size • Floor area • Stories • Parking ratio • Shop frontage and display windows • Rent roll • Lease contract type • Type of tenant • Vacancy rate

Table 7: Retail - property value determinants

Source: Author summarized and aggregated from Lin (2012); Beekmans, Beckers, Krabben, & Martens (2014); Monson (2009); RICS (2012); and DeLisle (2019)

Chapter 4: Empirical Research

Model specification or in the words, the use of the method in constructing AVMs is highly dependent on the data availability and characteristics of the data. The chapter illustrates the process of constructing AVMs for commercial properties using sales comparison approach and income approach in two totally different markets which are Los Angeles County (United States) and Finland.

4.1 The case of United States

4.1.1 Data description

The study examines physical characteristics, location and economic factors that influence office property values in Los Angeles County. The sample period for the analysis was from 2006 to 2018. The first dataset is obtained from Open Data of County of Los Angeles (County of Los Angeles, 2018) containing values and property physical characteristics for parcels on the Assessor's annual secured assessment rolls.

The study uses ordinary least squares (OLS) regression to analyze the relationship between property appraisal values from tax assessment and a number of independent variables from Chapter 3 which are believed to influence these values. The second set of data is locational characteristics. Coordinates of a city center where the property is located are drawn from realtR::geocode function (Bresler, 2019) in order to calculate the distance to the city center. A number of train stations and subway stations within Zip code area obtained from Google Places API (Cooley, 2018). The third set of data including economic factors are obtains from statistic sources such as GDP (U.S. Bureau of Economic Analysis, 2018a), HPI (U.S. Federal Housing Finance Agency, 2018b), new office construction (U.S. Bureau of Labor Statistics, n.d.), employment rate (Bureau of Labor Statistics, 2019a), inflation rate (Bureau of Labor Statistics, 2019b), people in related industry (Bureau of Labor Statistics, 2019c).

After filtering with office type property, the data is pre-processed including removing outliers, transform to nature logarithm form for property value and size variables, and grouping least frequent factor levels in categorical variables before constructing a model. The data after preprocessing contains 143 677 observations with 19 variables.

Explanations of dependent variables and independent variables after preprocessing are listed in Table 8:

Variable name	**Description**	**Type**
Log_totalvalue	Natural logarithm of property value	Continuous
Roll_year	Assessment roll year	Categorical
Floors	Number of floors in a property	Categorical
Property_use_code	Office type of property	Categorical
Year_built	Year built of property	Continuous
Log_size	Natural logarithm of property size	Continuous
City	City where a property is located	Categorical
Street_type	Type of street where a property is located	Categorical
Subway_station	Number of subway stations within property's zip code area	Categorical
Train_station	Number of train stations within property's zip code area	Categorical
Log_distance	Natural logarithm of distance from property to city center	Continuous
Population	The population of zip code area where the property is located	Continuous
Money_supply	The national total value of monetary assets available at a specific year.	Continuous
Employment_rate	The national percentage of the civilian noninstitutional labor force that is employed at a specific year	Continuous
GDP	National gross domestic product at a specific year	Continuous
HPI	The national housing price index	Continuous
Inflation_rate	National inflation rate at a specific year	Continuous
New_office_construction	National new office construction at a specific year	Continuous
People_in_related_industry	The national number of employee in Finance and Insurance industry/and Professional and Business Services at a specific year	Continuous

Table 8: Explanations of dependent variables and independent variables

Table 9 provides summary statistics of continuous variables using in the model:

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
year_built	139,001	1,966.048	22.644	1,827.000	1,951.000	1,983.000	2,018.000
log_totalvalue	139,508	13.631	1.501	10.001	12.566	14.522	18.199
log_size	139,508	8.615	1.469	4.382	7.597	9.461	13.647
money_supply_M1	139,508	2,378.778	803.276	1,373.008	1,638.092	3,021.733	3,685.717
GDP	139,508	16,584.800	2,037.015	13,814.610	14,712.840	18,219.300	20,226.490
HPI	139,508	353.523	33.029	309.613	322.808	375.655	419.140
employment_rate	139,508	0.600	0.016	0.584	0.586	0.604	0.631
inflation_rate	139,508	0.019	0.011	-0.004	0.015	0.028	0.038
new_office_construction	129,195	120.468	8.252	107.775	114.708	128.008	136.292
people_in_related_industry	139,508	23,682.970	1,509.769	21,834	22,432	24,490	26,326
log_distance	139,485	8.243	1.081	4.040	7.519	8.949	10.482
population	139,508	37,935.010	19,810.180	0	25,621.8	46,590	106,659

Table 9: Summary statistics of continuous variables

Frequency distributions of category variables are as follows:

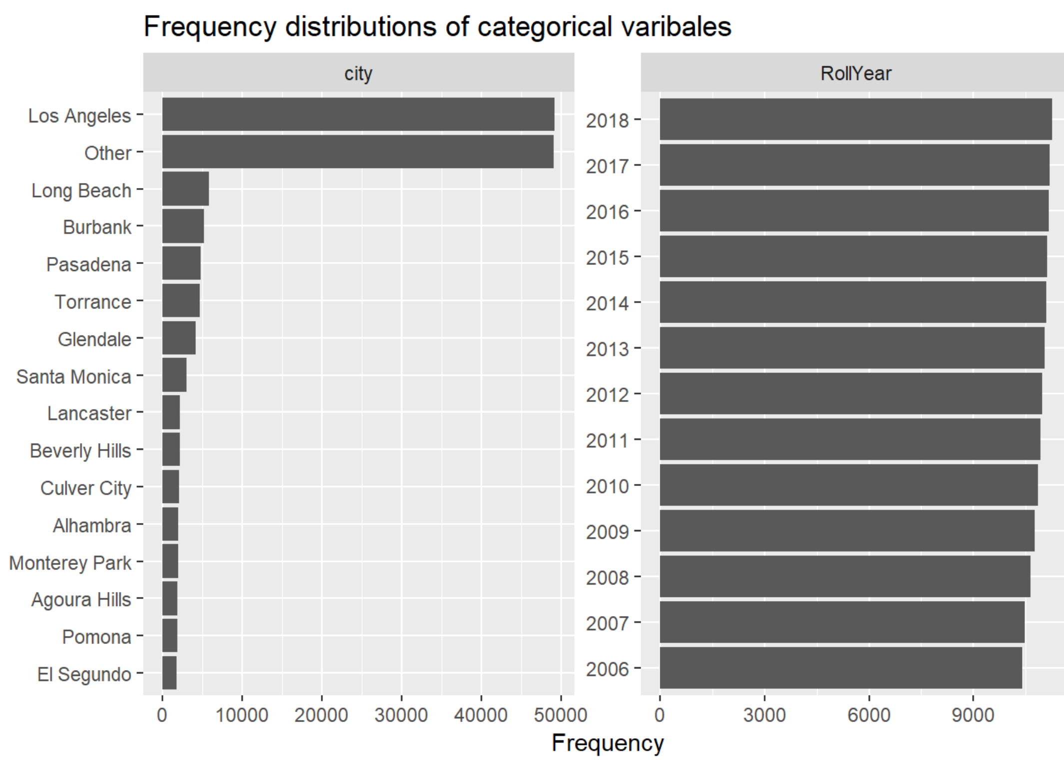

Figure 7: Frequency distribution of city and roll year variables

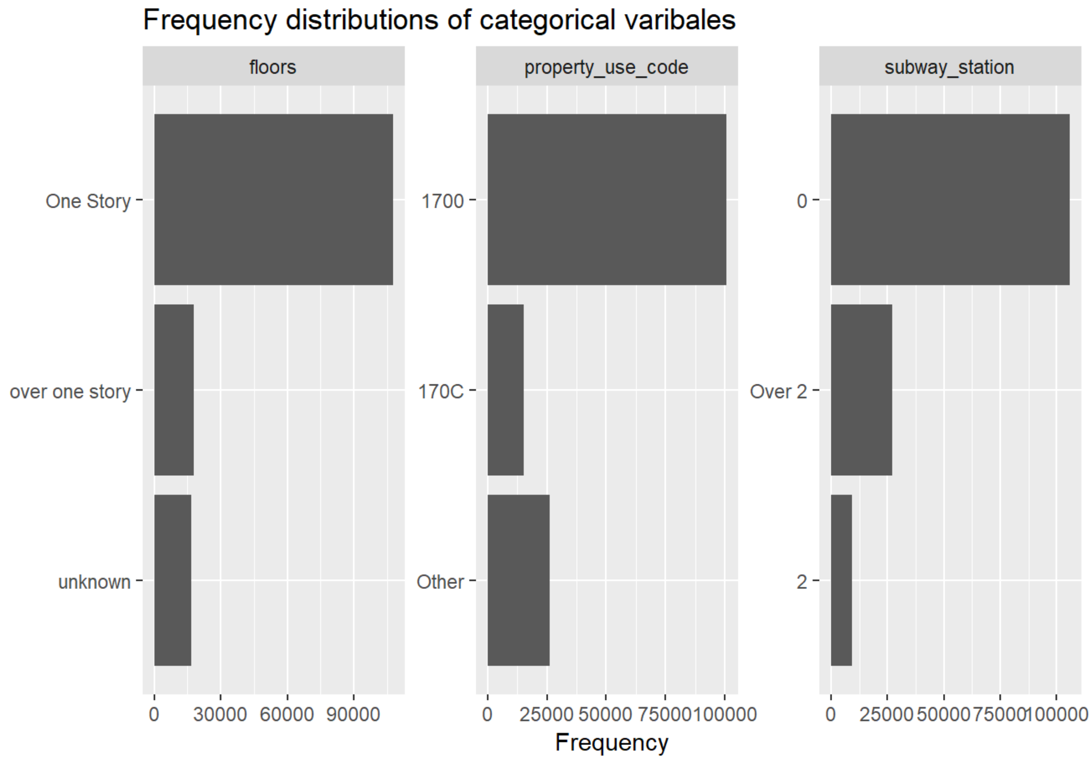

Figure 8: Frequency distribution of floors, property use code and number of subway stations

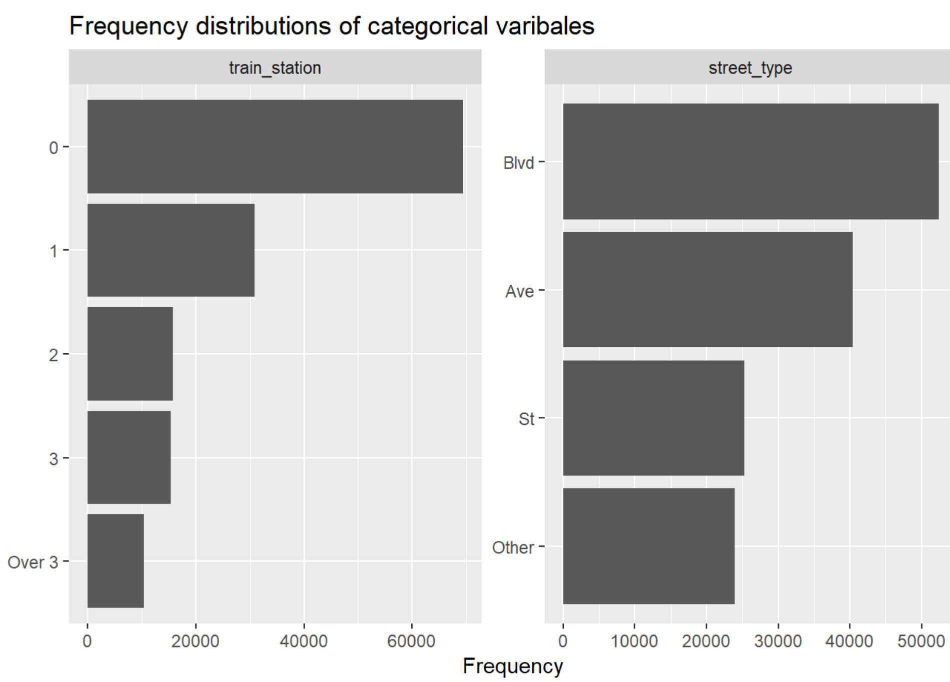

Figure 9: Frequency distribution of number of train stations and street type

4.1.2 Model specification and calibration

The data is split into two parts. One is used for training the model accounting for 80% of observations (111 606) and another is the test set with 20% of observations (27 902). The training test is used for constructing a model whereas the test set is only used to evaluate the accuracy of the model built from the training set.

In order to achieve the aim of this study, an AVM is built using multiple regression analysis. The goal of multiple regression analysis is to model the relationship between property values and property physical attributes, locational factors and economic factors. Therefore, office property values could be predicted based on above-mentioned independent variables. The functional form of the model is as follows;

$$ln(total\_value) = b_0 + b_1 \ x \ ln(size) + b_2 \ x \ RollYear + b_3 \ x \ floors + b_4 \ x \ property\_use\_code + b_5 \ x \ year\_built + b_6 \ x \ city + b_7 \ x \ street\_type + b_8 \ x \ subway\_station + b_9 \ x \ train\_station + b_{10} \ x \ ln(distance) + b_{11} \ x \ population + b_{12} \ x \ money\_supply\_M1 + b_{13} \ x \ GDP + b_{14} \ x \ HPI + b_{15} \ x \ employment\_rate + b_{16} \ x \ inflation\_rate + b_{17} \ x \ new\_office\_construction + b_{18} \ x \ people\_in\_related\_industry$$

After running a regression on training data and removing variables statistically insignificant as well as excluding variables that are correlated with each other (i.e. multicollinearity), ten variables are statistically significant and hence, are used in the model. The results in Table 10 provides beta coefficient estimates associated with each independent variables. The standard error is reported in brackets.

Model result

	Dependent variable:
	log_totalvalue
property_use_code170C	0.103***
	(0.007)
property_use_codeOther	0.090***
	(0.005)
year_built	0.006***
	(0.0001)
log_size	0.899***
	(0.001)
street_typeBlvd	0.055***
	(0.004)
street_typeOther	0.060***
	(0.005)
street_typeSt	-0.029***
	(0.005)
subway_station2	0.202***
	(0.008)
subway_stationOver 2	0.096***
	(0.005)
train_station1	-0.092***
	(0.004)
train_station2	-0.130***
	(0.006)
train_station3	-0.249***
	(0.006)
train_stationOver 3	-0.255***
	(0.007)
employment_rate	-3.025***
	(0.104)
people_in_relate_industry	0.0001***
	(0.00000)
log_distance	-0.014***
	(0.002)
population	-0.00001***
	(0.00000)
Constant	-5.036***
	(0.179)
Observations	111,185
R^2	0.864
Adjusted R^2	0.864
Residual Std. Error	0.554 (df = 111167)
F Statistic	41,570.690*** (df = 17; 111167)
Note:	*p<0.1;* ***p<0.05;*** p<0.01

Table 10: Model regression results

Coefficient of determination (R^2) of the model is 0.864 meaning that ten variables representing property physical characteristics, locational characteristics and economic factors explained 86.4% of the values of office properties. In other words, only 13.6 % in the observed relationships are not explained by ten independent variables in this study.

Figure under below indicates the relationship between the log property values versus log size.

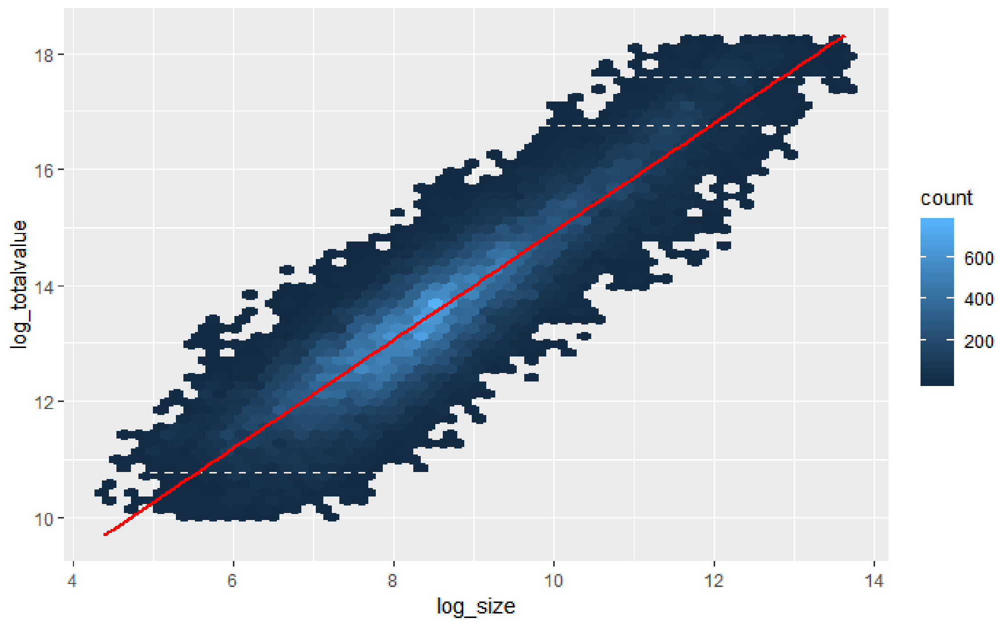

Figure 10: Relationship between the log property values versus log size

Table 11 presents the generalized variance inflation GVIF) of each variable. According to the rule of thumb that a variance inflation factor above 10 indicates multicollinearity in the regression (Fehribach, Rutherford, & Eakin, 1993). The result shows that no variable has GVIF more than 10, meaning there is no multicollinearity in the model.

Variable	GVIF	Df	GVIF^(1/(2*Df))
property_use_code	1.771907	2	1.153746
year_built	1.362081	1	1.167082
log_size	1.719099	1	1.311068
street_type	1.104467	3	1.016698
subway_station	1.607770	2	1.126046
train_station	1.510697	4	1.052924
employment_rate	1.007111	1	1.003549
people_in_related_industry	1.008778	1	1.004379
log_distance	1.061493	1	1.030288
population	1.197650	1	1.094372

Table 11: Generalized variance inflation GVIF of each variable

4.1.3 Model validation

This section focuses on how predictive performance the model could achieve by running the model on 5 different cities from the test set. Since the model predicted the property value in natural logarithm, estimated property values were transformed back to real value in order to calculate the individual forecast standard deviation (FSD).

Table 12 presented the first 20 rows of test set after running the model.

Case no	Log predicted value	Predicted value	Benchmark value	Error	Absolute error	% Error
(1)	(2)	(3) = $e^{(2)}$	(4)	(5) = (3) – (4)	(6)	(6) / (4) x100
1	11.67997	118181	110142	8038.972	8038.972	7.298734
2	11.7702	129339.4	136203	-6863.63	6863.629	5.039264
3	11.77515	129981.3	115974	14007.29	14007.29	12.07795
4	11.89341	146299.5	130638	15661.47	15661.47	11.98845
5	11.89341	146299.5	128181	18118.47	18118.47	14.13506
6	11.93076	151867.1	130741	21126.07	21126.07	16.15872
7	11.93252	152134.4	121000	31134.37	31134.37	25.73088
8	11.98672	160607.4	180000	-19392.6	19392.63	10.77369
9	12.0098	164357.6	149632	14725.56	14725.56	9.841186
10	12.06149	173076.4	163342	9734.352	9734.352	5.959491
11	12.09136	178325.1	168000	10325.07	10325.07	6.145876
12	12.11185	182016.7	149000	33016.71	33016.71	22.15887
13	12.1299	185331.9	189600	-4268.14	4268.138	2.251128
14	12.1492	188943.6	163935	25008.57	25008.57	15.25518
15	12.19192	197189.4	169910	27279.35	27279.35	16.05518
16	12.22376	203568.1	226378	-22809.9	22809.92	10.07603
17	12.33686	227945.1	210000	17945.07	17945.07	8.54527
18	12.35966	233200.9	228887	4313.913	4313.913	1.884735
19	12.47978	262966.6	261119	1847.626	1847.626	0.70758
20	12.48567	264520.6	249617	14903.6	14903.6	5.970588

Table 12: First 20 rows results of test set after running the model

Table 13 provides the FSD of a model on a city level. The forecast standard deviation is about 30% indicating the model predicts property value quite well in these five cities.

City	**No**	**Mean of variance**	**Median of variance**	**FSD city**
Agoura Hills	393	32.14460	17.78529	32.22661
El Segundo	366	31.26154	27.35096	31.34719
Glendale	808	38.98614	25.30322	36.01271
Monterey Park	395	33.8914	33.53703	35.22829
Torrance	824	33.81322	24.75306	33.85430

Table 13: FSD of a model on a city level

Overall, RMSE and MAPE for test set in these five cities are $2,727,813 and 33.94% respectively.

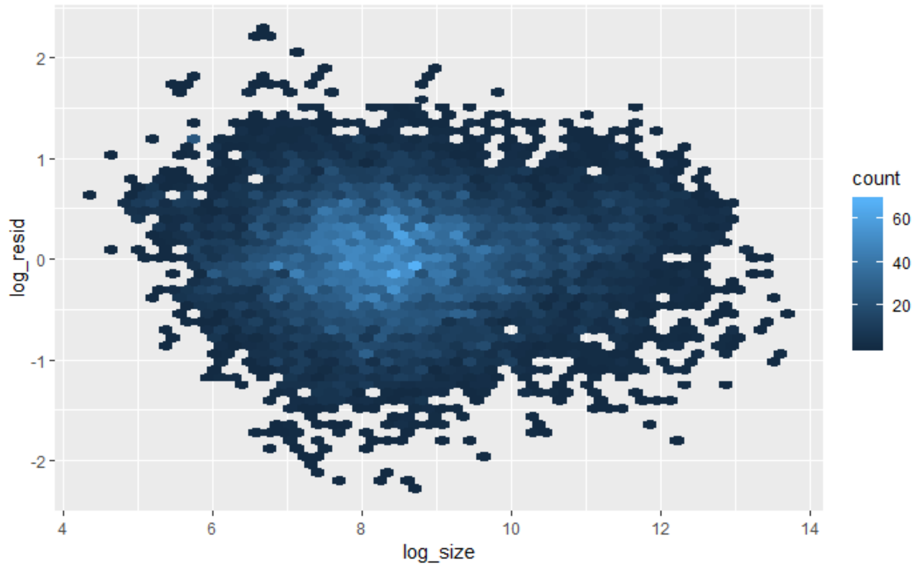

Figure 11: Plot of residuals (logarithm form) on test set

Examining the residuals plot in the Figure 11, there was no linear pattern in the residual plot.

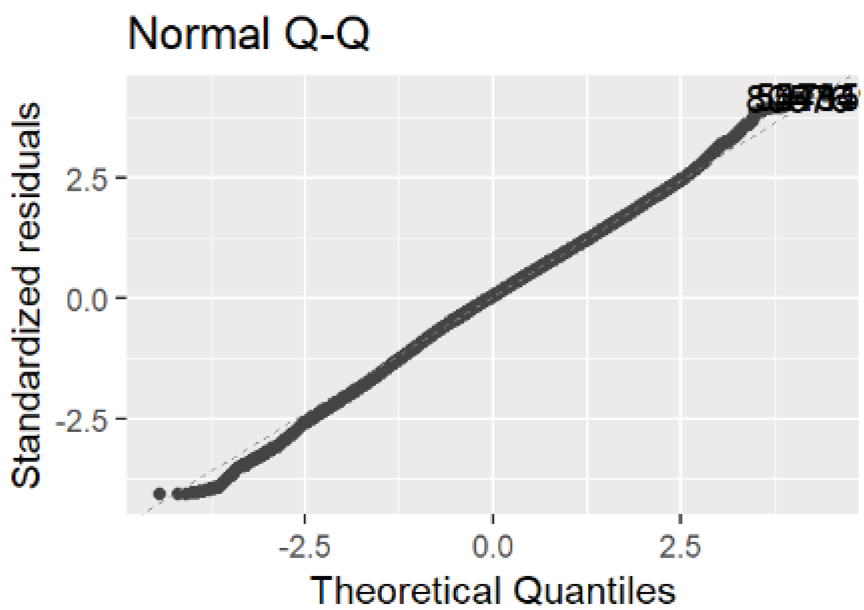

Figure 12: Normal Q-Q plot

The normal Q-Q plot shows that most of the residuals follows the straight dash-line, indicates that they are normally distributed.

4.2 The case of Finland

4.2.1 Data description

The data in Table 14 in the below documented 12 transactions for office type in Finland in 2018 recorded by S&P Global Market Intelligence (n.d.). As opposed to the US market in the previous section, data captured from Finland having few transactions along with the poor attributes of the data. Apart from the location, the building characteristics include only the size of the buildings. Consequently, the absence of sales comparables renders the application of AVMs that use the sales comparison approach in Finland.

Meanwhile, occupancy rates of given buildings are included in the dataset. Moreover, rental information and yields of comparable properties that are in the same neighborhood are more available than that of the comparable sales price. In addition, capital expenditure estimation based on the technical calculation of building components derived from SkenarioLabs, a leading data analytics service for property in Finland, are also available. Therefore, developing an AVM based on income approach would be suitable in this case.

Although when it comes to the income approach, most of the AVMs for commercial real estate using the direct capitalization method (Tretton, 2007). The automation comes from the program which determines “the yield for the individual property according to its property attributes” (Tretton, 2007, p. 488). However, direct capitalization should be used with caution because estimating property values based on NOI for only one year could be proved problematic (Brueggeman & Fisher, 2008, p. 288). Therefore, this second empirical study proposes the use discounted cash flow (DCF) method in the process of developing AVM.

S&P Global
Market Intelligence

Property Transactions

Property Type Other Retail, Regional Mall, Shopping Center, Industrial, Office
Transaction Type Acquisition
Date Range 01/01/2018 - 31/12/2018
Country Finland

Property Transaction for Finland								
Property Type	*Property Name*	*Address*	*Acquisition Price (€000)*	*Portfolio Acquisition?*	*Portfolio Acquisition Price (€000)*	*Other Size*		*Occupancy rate (%)*
						Size	*Unit of Measurement*	
Office : Unclassified	(1) Kuopion Kauppakeskus	Kauppakatu 39, Kuopio, Pohjois-Savo 70100	7,600	Yes	254,800	4,832	sq. m.	98.50 As of 31/08/2019
Office : Unclassified	(2) Mäkitorpantie 3	Mäkitorpantie 3, Helsinki, Uusimaa 00620	7,600	Yes	254,800	4,367	sq. m.	85.60 As of 31/08/2018
Office : Unclassified	(3) Liiketalo Myyrinraitti	Myyrmäenraitti 2, Vantaa, Uusimaa 01600	12,000	Yes	254,800	7,515	sq. m.	94.10 As of 31/08/2018
Office : Unclassified	(4) Opus 1	Hitsaajankatu 24, Helsinki, Uusimaa 00810	13,500	Yes	254,800	6,821	sq. m.	77.10 As of 31/08/2018
Office : Unclassified	(5) Pakkalan Kartanonkoski 12	Pakkalankuja 7, Vantaa, Uusimaa 01510	6,100	Yes	254,800	3,425	sq. m.	100.00 As of 31/08/2018
Office : Unclassified	(6) Pakkalan Kartanonkoski 3	Pakkalankuja 6, Vantaa, Uusimaa 01510	9,700	Yes	254,800	7,796	sq. m.	77.20 As of 31/08/2018
Office : Unclassified	(7) Plaza Forte	Äyritie 12c, Vantaa, Uusimaa 01510	12,600	Yes	254,800	6,054	sq. m.	96.90 As of 31/08/2018
Office : Unclassified	(8) Plaza Allegro	Äyritie 8b, Vantaa, Uusimaa 01510	11,200	Yes	254,800	4,620	sq. m.	91.70 As of 31/08/2018
Office : Unclassified	(9) Plaza Vivace	Äyritie 8c, Vantaa, Uusimaa 01510	13,200	Yes	254,800	5,661	sq. m.	88.30 As of 31/08/2018
Office : Unclassified	(10) Purotie 1	Purotie 1, Helsinki, Uusimaa 00380	7,100	Yes	254,800	4,692	sq. m.	97.20 As of 31/08/2018
Office : Unclassified	(11) Salmisaarenaukio 1	Salmisaarenaukio 1 Helsinki, Uusimaa 00180	80,777	No	NA	14,433	sq. m.	100.00 As of 23/01/2019
Office : Unclassified	(12) Grandinkulma	Kielotie 7, Vantaa, Uusimaa 01300	12,500	Yes	254,800	6,189	sq. m.	98.40 As of 31/08/2018

Table 14: Commercial property transactions in Finland from 01/01/2018 to 31/12/2018

4.2.2 Model specification

The model is designed to estimate the value of the property unit as a basic valuation of a whole property. Property unit is determined by tenants and use of properties. The underlying reason for it is that commercial properties are highly heterogeneous. All of the variable inputs varies such as yield and vacancy rate varies from one type to another even though they are located in the same location. Therefore, in author's opinion, it is more accurate and sensible to assess a property unit and choose necessary variables such as yield and discount rate according to its use. The value of the whole property is equal to the sum of all property units within a property. The model can also evaluate the property value of the property group or portfolio using the same concept.

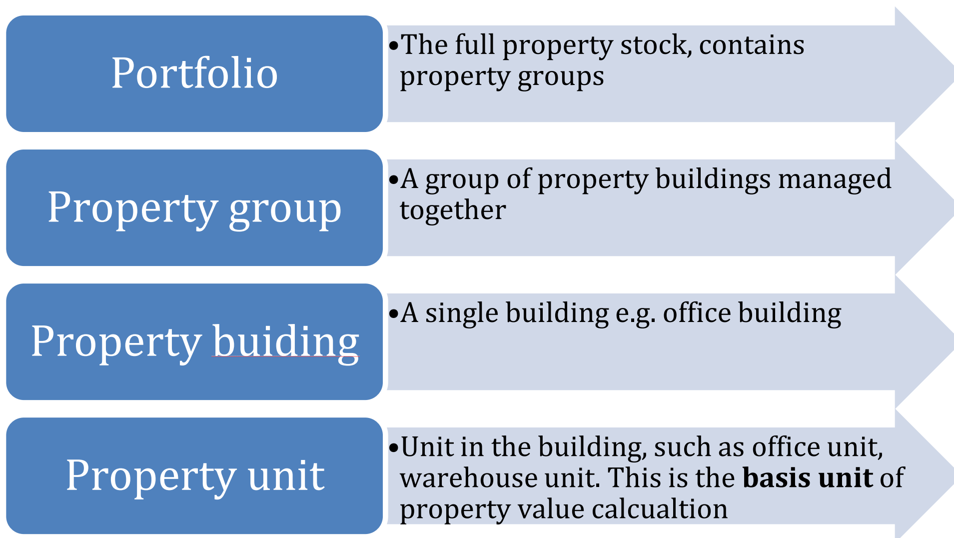

Figure 13: SkenarioLabs property view's structure

(SkenarioLabs, 2019a)

The model uses pre-tax cash flows, parameters and assumptions of AVM are defined as follows:

Time horizon:

The model takes into account pre-tax cash flow during ten-year holding period.

Monthly rent:

Gross monthly rent. This is provided by clients.

Annual potential gross income:

$Year_i = Monthly\ rent \times 12 \times (1 + rental\ growth\ rate)$

The rental growth rate is assumed to grow with the inflation rate that is forecasted as 1.37% per year. This is derived from 10-year average inflation in Finland from 2011 to 2020

	2011	2012	2013	2014	2015	2016	2017	2018	2019*	2020*
Inflation (%)	3.4	2.8	1.5	1	-0.2	0.4	0.7	1.1	1.4	1.6

Table 15: Inflation in Finland

(Source: KTI, 2018 & KTI, 2019)

Occupancy rate:

Based on the existing lease term of the current property.

Effective gross income (EGI)

EGI_i = *Annual potential gross income$_i$ x occupancy rate$_i$*

Operating expense (OPEX) growth rate:

The OPEX growth rate is assumed to be 2.1% year-on-year (Official Statistics of Finland, 2018)

Operating expense (OPEX)

OPEX is based on tenant's information. If the OPEX is unknown, the model uses OPEX per square meter according to operating cost statistics for certain property types including office, retail and logistics multiply by unit floor area. OPEX per square meter are 3.96, 3.69 and 3.21 for office, retail and industrial respectively. (Kumpula, 2017)

$OPEX_i = Annual\ OPEX_{i-1} \times (1 + OPEX\ growth\ rate)$

Net Operating income (NOI):

Income after deducting the operating cost

$NOI_i = EGI_i - OPEX_i$

Capital expenditure (CAPEX)

CAPEX per year is provided by SkenarioLabs Ltd. – a leading data analytics service for property in Finland. The renovation forecasts are based on SkenarioLabs data analytics of similar property and construction components. Predefined renovation costs are estimated for all building components which are categorized as four types i.e. part *change (replace the old part with the new one), miscellaneous (repair some damages on a current one), window sealing and roof painting.*

Cash flows:

Cash flows (CF_i) after excluding capital expenditure.

$CF_i = NOI_i - CAPEX_i$

Terminal value (TV): the value of a property in question at year 10th and is estimated assuming that the rent roll will grow indefinitely.

$$TV = \frac{EGI_{11}}{Y_t} - \frac{OPEX_i}{Y_t - (OPEX\ growth\ rate - g)} - stabilized\ CAPEX$$

Stabilized CAPEX is assumed to be average CAPEX from the 1st year to the 10th year

Y_t is exit yield, g is inflation

Exit yield: is derived by adjusting yield or going-in cap rate. Although there are many ways to derive exit yield, Brueggeman & Fisher (2008, p. 292) show the common pattern in their example to derive exit yield in real estate valuation is adding 1% to yield for 10-year holding period. This is based on the assumption that market will be eventually equilibrium. The difference between yield and exit yield reflects the building obsolescent, thus exit yield is higher than yield.

Exit yield (Y_t) = yield + 1%

Selling free is assumed to be 1% of Terminal value

Selling free = TV x 1%

Market value of the property is equal to the total present value of cash flows generated from property

$$\frac{CF_1}{1 + discount\ rate} + \frac{CF_2}{(1 + discount\ rate)^2} + \cdots + \frac{CF_{10} + TV - Selling\ fee}{(1 + discount\ rate)^{10}} +$$

Yield

Derived from similar property types and it location

Discount rate:

Discount rate = Yield + Inflation

4.2.4 Model validation

With this model specification in the above, rental incomes are compulsory in order to use this model. Unfortunately, in Table 14, there was no rental value provided in the original dataset. For this reason, author would find similar rental values from listing information associated with the property in order to conduct the study. In addition, yields were documented from market reports based on the similarity between property type and location.

Rent per square meter of the case (11) is €29/sqm/month (or 5 million euros per annum for the property) which was the actual rent associated with the given property reported by Castellum (Cision, 2018).

Case (4) uses the rent of €18/sqm/month, which is average rent per square meter in the advertisement of this property, listed on Cushman &Wakefield's website (Cushman & Wakefield, 2019a).

Similarly, rent per square meter of the case (12) is €18/sqm/month, which is the average rent in advertisement drawn from this subject property captured by Cushman & Wakefield (Cushman & Wakefield, 2019b).

Case (5), (7), (8), and (9) have the rent of €20.5/sqm/month which is the average office rent of Aviapolis area (Newsec, 2016, p. 17).

Case (6) uses €16/sqm/month, starting office rent in Aviapolis area (Newsec, 2016, p. 17).

Case (3) uses €16/sqm/month drawn from similar property located in the same postcode 00620 (toimitilat.kauppalehti.fi, 2019)

Table 16 presents yields and rent level in the given market area. Yield/income returns of all cases excluding (11) are 6.5% which are drawn from office class in Finland (KTI, 2019, p. 50). Yield of the case (11) – i.e. 5.5% is the average of yield properties located in Helsinki city center (Newsec, 2016, p. 21).

No	Address	Yield (%)	Rent (€/sqmt)	Exit Yield (%)
1	Kauppakatu 39, Kuopio, Pohjois-Savo 70100	6.5	14	7.5
2	Mäkitorpantie 3, Helsinki, Uusimaa 00620	6.5	16	7.5
3	Myyrmäenraitti 2, Vantaa, Uusimaa 01600	6.5	12.5	7.5
4	Hitsaajankatu 24, Helsinki, Uusimaa 00810	6.5	18	7.5
5	Pakkalankuja 7, Vantaa, Uusimaa 01510	6.5	20.5	7.5
6	Pakkalankuja 6, Vantaa, Uusimaa 01510	6.5	16	7.5
7	Äyritie 12c, Vantaa, Uusimaa 01510	6.5	20.5	7.5
8	Äyritie 8b, Vantaa, Uusimaa 01510	6.5	20.5	7.5
9	Äyritie 8c, Vantaa, Uusimaa 01510	6.5	20.5	7.5
10	Purotie 1, Helsinki, Uusimaa 00380	6.5	17.5	7.5
11	Salmisaarenaukio 1 Helsinki, Uusimaa 00180	5.5	29	6.5
12	Kielotie 7, Vantaa, Uusimaa 01300	6.5	18	7.5

Table 16: Yields, exit yields, and rent level for properties

CAPEX forecasts from 2019 to 2028 associated with given property based on different components of the buildings (SkenarioLabs, 2019) are given the Table 17.

No	*Address*	*CAPEX 2019 (€000)*	*CAPEX 2020 (€000)*	*CAPEX 2021 (€000)*	*CAPEX 2022 (€000)*	*CAPEX 2023 (€000)*	*CAPEX 2024 (€000)*	*CAPEX 2025 (€000)*	*CAPEX 2026 (€000)*	*CAPEX 2027 (€000)*	*CAPEX 2028 (€000)*
1	Kauppakatu 39, Kuopio, Pohjois-Savo 70100	0	249	0	0	0	0	29	0	0	0
2	Mäkitorpantie 3, Helsinki, Uusimaa 00620	0	0	0	0	0	0	0	0	0	0
3	Myyrmäenraitti 2, Vantaa, Uusimaa 01600	0	553	0	0	0	0	87	0	0	0
4	Hitsaajankatu 24, Helsinki, Uusimaa 00810	0	0	0	0	70	0	0	0	0	96
5	Pakkalankuja 7, Vantaa, Uusimaa 01510	0	0	0	0	0	0	0	0	0	0
6	Pakkalankuja 6, Vantaa, Uusimaa 01510	0	0	0	0	0	0	0	0	0	0
7	Äyritie 12c, Vantaa, Uusimaa 01510	0	0	0	90	0	0	0	0	0	0
8	Äyritie 8b, Vantaa, Uusimaa 01510	0	103	0	0	0	0	143	0	0	0
9	Äyritie 8c, Vantaa, Uusimaa 01510	0	0	0	0	65	0	0	0	0	90
10	Purotie 1, Helsinki, Uusimaa 00380	0	0	48	0	0	139	0	425	0	0
11	Salmisaarenaukio 1 Helsinki, Uusimaa 00180	0	0	0	135	0	0	0	0	0	188
12	Kielotie 7, Vantaa, Uusimaa 01300	541	0	0	0	0	85	0	0	0	0

Table 17: CAPEX forecasts from 2019 to 2028 associated with a given property (SkenarioLabs, 2019)

No	***Address***	***Acquisition Price (€000)***	***Estimation (€000)***	***Error (€000)***	***Absolute error (€000)***	***(%) Error***
		(1)	(2)	(3) = (2) - (1)	(4)	(4) / (1)
1	Kauppakatu 39, Kuopio, Pohjois-Savo 70100	7,600	6,342	(1,258.22)	1,258.22	17%
2	Mäkitorpantie 3, Helsinki, Uusimaa 00620	7,600	7,075	(524.86)	524.86	7%
3	Myyrmäenraitti 2, Vantaa, Uusimaa 01600	12,000	7,588	(4,411.88)	4,411.88	37%
4	Hitsaajankatu 24, Helsinki, Uusimaa 00810	13,500	13,056	(444.48)	444.48	3%
5	Pakkalankuja 7, Vantaa, Uusimaa 01510	6,100	7,911	1,810.97	1,810.97	30%
6	Pakkalankuja 6, Vantaa, Uusimaa 01510	9,700	12,631	2,930.59	2,930.59	30%
7	Äyritie 12c, Vantaa, Uusimaa 01510	12,600	13,913	1,312.68	1,312.68	10%
8	Äyritie 8b, Vantaa, Uusimaa 01510	11,200	10,487	(713.04)	713.04	6%
9	Äyritie 8c, Vantaa, Uusimaa 01510	13,200	12,982	(218.36)	218.36	2%
10	Purotie 1, Helsinki, Uusimaa 00380	7,100	8,293	1,193.19	1,193.19	17%
11	Salmisaarenaukio 1 Helsinki, Uusimaa 00180	80,777	83,737	2,960.45	2,960.45	4%

12	Kielotie 7, Vantaa, Uusimaa 01300	12,500	11,339	(1,160.61)	1,160.61	9%

Table 18: Model results

Table 18 shows the results of the model. With the estimation above, RMSE and MAPE of the model are 1.983.000 € and 14% respectively. Overall FSD is 19.2%.

Among all, case (3) has the highest error i.e. 37%. The reason might be because the rental income that author used in the model was drawn from rent advertisement of the same property type (i.e. office) within a postal code. This would be problematic since this rent (i.e. 16/sqm/month) ignores the difference between property physical attributes. Rents might vary significantly from one office to another due to differences in building physical characteristics, even though they are located in the same area. Once the rental income is not accurate, the valuation estimation is affected as well.

The automation in the property valuation process is in the program using the DCF framework which estimates property value based on property parameters. In practice, for conducting this secondary empirical case, inputs that are used in DCF and model specification were converted to an application programming interface (API) using R (programing language). After acquiring necessary information such as rent and expenses, author uploaded a file containing above-mentioned properties to the API server. The process of getting property value predictions took less than a minute.

It is important to notice that the most important inputs and compulsory are property's finance information such as rental incomes and costs for predicting cash inflows and outflows. Those are the key to valuation accuracy. In general, an AVM using the income approach, in fact, is a combination of "sub" AVMs. Each "sub" AVM predicts components that are used in the main AVM. According to Gloudemans & Almy (2011, p. 339), steps in income approach include "(1) estimate potential gross income (PGI), (2) apply vacancy and collection losses to obtain effective gross income (EGI), (3) subtract allowable expenses to obtain net operating income (NOI), and (4) capitalize NOI by applying an appropriate overall capitalization rate". As a result, the analyst would build different models for predicting PGI, expense models, and overall capitalization rate models in order to predict property values.

Chapter 5: Conclusion

This chapter will summarize findings of the study. The first section presents the key findings of the study. The research results are discussed in the next section. After that, the quality and reliability of the research are assessed. Finally, the chapter ends with proposing topics for future research regarding developing Automated Valuation Models for commercial real estate.

5.1 Key Findings and discussion

This research first investigates relevant parameters that should be used in AVMs models drawn from existing literature. After which, the first empirical case shows that all three group of factors such as building physical attributes, locational and economic factors play important roles in the formation of property values. The second empirical case shows property's finance information such as cash inflows, cash outflows, vacancy rates are the key for an accurate valuation. It is important to notice that in the second study although building physical attributes, locational and economic factors are not explicitly included in the model, those factors are reflected indirectly through property's finance information. In greater details, property cash flows reflect the physical attributes of the buildings. For instance, the higher the rental level is, the better location/ or bigger size of the building is. Locational and economic factors reflect through the vacancy rates and rental growth rates. Property yield reflects the risk of the whole market (risk-free rate) and specific property (risk premium).

Secondly, this research demonstrates ways to develop AVMs for commercial real estate. The research shows that for a market that has many comparable sales available, sales comparison approach using regression methods are good way to develop AVMs. By contrast, for not very transparent commercial real estate market like Finnish, according to Kiviluoto (2017, slide 23), where the most important source of information comes from internal data, active interaction with clients and other parties, AVMs could be developed by applying traditional discounted cash flows technique by utilizing more available data such as rent rolls and expenses. Therefore, this could be a starting point to tackle problem regarding commercial property data limitation in non-transparent real estate markets. The main model based on discounted cash flow is the backbone of valuation. The more detailed and accurate inputs the model receives, the most likely market value it could produce.

In the first empirical study, when using AVM to predict property values in the hold-out sample (i.e. test set) for five cities, the model coefficient of dispersion (COD) is shown in Table 19. COD of 36% and FSD of city level is about 30% (as presented in Table 13) indicate fairly good performance of the model. In addition, the plot of residuals and Q-Q plot in Figure 11 and Figure 12 were examined, indicating that the model captured well linear relationship from the data.

Case no	Predicted value ($)	Benchmark value ($)	Ratio	Absolute difference from the median
	(2)	(3)	(2)/(3)	
1	118,181	110,142	1.07	0.15
2	129,339	136,203	0.95	0.02
3	129,981	115,974	1.12	0.19
…	…	…	…	…
1603	541,906	632,900	0.86	0.07
1604	61,322	107,103	0.57	0.35
1605	198,211	261,252	0.76	0.17
				536.25
Mean of ratio = 1.05 Median of ratio = 0.93 Average deviation = 536.25 / 1605 = 0.334 COD = 0.334 /0.93 x 100 = 36% 95% confidence interval = 1.05 +/- 0.02				

Table 19: Model evaluation (the first empirical case)

In the second empirical case, due to the nature of the local market and lack of comparable transactions,the income approach was used to develop AVMs. Although direct capitalization is popularly used in the income approach, the second empirical case takes a different way which is using DCF. COD of the results is regarded in the below;

Case no	Acquisition Price (€000)	Estimation (€000)	sale ratio	Absolute difference from the median
	(1)	(2)	(2)/(1)	
1	7,600	6,342	0.83	0.14
2	7,600	7,075	0.93	0.04
3	12,000	7,588	0.63	0.34
4	13,500	13,056	0.97	0.01
5	6,100	7,911	1.30	0.32
6	9,700	12,631	1.30	0.33
7	12,600	13,913	1.10	0.13
8	11,200	10,487	0.94	0.04
9	13,200	12,982	0.98	0.01
10	7,100	8,293	1.17	0.19
11	80,777	83,737	1.04	0.06
12	12,500	11,339	0.91	0.07
				1.68
Median = 0.98				
Average deviation = 1.68 / 12 = 0.14				
COD = 0.14 / 0.98 x 100 = 14.3%				

Table 20: Coefficient of Dispersion (the second case)

Due to significant amounts of information considered into valuation, including rental values, lease term, vacancy rates, expenses, employment rates, GDP, demographics, property size, year built, condition, proximity to local amenities, and so on, property valuation is not a simple work that a single person could achieve fast and at ease. Especially, if more comparable sales are used in the valuation, the process quickly becomes complicated. AVMs are useful tools for appraisers in this sense since it combines the computational power and statistical approach. The accuracy of AMVs could be enhanced by allocate the risk to a significant number of transaction (Williams, 2018).

5.2 Validity, reliability and limitations of the research

5.2.1 Validity

The empirical research comprises two practical cases in different markets and demonstrates step-by-step developing AVMs. Model variables that influence to office property values are selected based on the existed theoretical framework drawn from the literature review. Model development processed followed guideline of IAAO (2018). After which the validity of the models was carefully tested with a large test set for five different cities in the US and twelve individual transactions in Finland. Model performances are evaluated using primary test statistic i.e. forecast standard deviation.

5.2.2 Reliability

The main limitations of the research are the former case study using multiple regression analysis (MRA) which requires strictly certain assumptions. Those most important are a linear relationship between predicted and explanatory variables, additivity, normal distribution of errors, uncorrelated independent variables, sample representativeness (IAAO, 2003). However, the world data is neither always linear nor met those assumptions. Therefore, MRA fails to capture the nuanced interdependencies and hence might ignore some important variables that influence commercial property values.

The latter case has a limitation regarding providing inputs to the model. The most important is the actual rental values of the property. In the empirical case, the exact rental value of the property is not available, hence the model uses rental information rent per square meter of comparable. However, comparable under research was only considered in a similar location (i.e. postal code) and property type. The set of physical building attributes was not considered due to limited comparable data. The second limitation is OPEX per square meter was used in the model is drawn from statistics information. This might not reflect the true operating cost which associated with the property under research. It is also important to notice that in order use the model specified in section 4.2 in particular and income approach in general, separated models, for example, gross income models and overall rate models are needed (Gloudemans & Almy, 2011, Chapter 9, pp. 339-361). Nonetheless, this second empirical study did not cover these two above-mentioned models due to the lack of lease and sales.

5.3 Further Research

When using the sales comparison approach to develop AVMs, an analyst could use more advanced Machine learning algorithms which do not requires linear assumption, and thus could capture more non-linear relationship between property value and explanatory variables. Although FSD result from this study was about 30% in large test for the US market, there is still more room to improve the total error to plus or minus 10% before it could be used commercially.

Another interesting topic to develop further an AVM using income model for the case of Finland is that the analyst could model input variables such as rental levels or OPEX or rental incomes. As indicated in section 5.1, the more detailed and accurate inputs the model receives, the most likely market value it could estimate. By improving the accuracy of inputs variables, the model performance could be significantly enhanced.

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